Regional Dominance and Industrial Success: A Productivity-Based Analysis

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ABSTRACT

Joshua Drucker: Regional Industrial Dominance and Business Success:
A Productivity-Based Analysis
(Under the direction of Edward J. Feser)

The relationship between industrial structure and economic performance has long interested researchers in regional science, industrial economics, and economic development. Research on the subject, however, has largely overlooked the influence that regional industrial dominance—regional concentration within a specific industry—may have upon smaller local firms in that industry. This dissertation investigates the links between regional industrial dominance, agglomeration economies, and firm performance for selected U.S. industries, focusing on two main hypotheses: 1) plants in regional industries dominated by a few relatively large firms are less productive than establishments in the same industry located in other regions; 2) small establishments in dominated regional industries are less productive because they are limited in their ability to take advantage of regionally available external economies.

Confidential micro-level data from the United States Census Bureau are used to estimate a cross-sectional production system at the plant level for three manufacturing sectors: rubber and plastics, metalworking machinery, and measuring and controlling devices. The models incorporate indicators of regional industrial dominance, spatially attenuating measures of agglomeration economies, and controls for other relevant

establishment and regional characteristics. Estimating production functions at the establishment level serves to address many of the methodological drawbacks of earlier production function work and supports direct tests of the research hypotheses.

The primary finding is that regional industrial dominance has substantial negative impacts on production, especially for small, dominated establishments. There is little evidence to support the second hypothesis that the diminished productivity of dominated businesses stems from reduced capacity to exploit localized agglomeration economies. The results demonstrate the importance of regional industrial dominance as a determinant of establishment productivity, and indicate that analysts and policymakers should examine regional industrial structure as a key component of the external environment that helps shape business performance and regional economic adaptability. Further research will be required to understand the precise mechanisms by which regional industrial dominance acts to influence economic performance and to guide the design of appropriate policies for economic development.

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study have been screened to ensure that no confidential data are revealed. All contents and conclusions expressed are solely my responsibility and do not necessarily reflect the views of any of the supporting organizations or the United States Census Bureau.

TABLE OF CONTENTS

List of Tables xii

List of Figures xvi

1. Introduction 1

1.1. Overview 1

1.2. Research Significance 3

1.3. Policy Significance 4

1.4. Organization 6

2. Regional Industrial Dominance, Industrial Organization, and Agglomeration 7

2.1. Introduction 7

2.2. The Concept of Regional Industrial Dominance 8

2.3. Firm and Establishment Size Distributions 10

2.4. Agglomeration Economies 18

2.4.1. The Theory of Agglomeration Economies 19

2.4.2. Empirical Studies of Regional Agglomeration Economies 23

2.4.2.1. Size, Density, and Productivity 24

2.4.2.2. Urbanization versus Localization 26

2.4.2.3. Marshall-Arrow-Romer, Jacobs, and Porter Externalities 36

2.4.2.4. Knowledge Spillovers 42

2.4.2.5. Marshall's Agglomeration Economies 47

2.4.2.6. Summary of Empirical Agglomeration Research 52

2.5. Two Key Studies of Regional Industrial Organization 54

2.6. Summary 59

3. Conceptual Framework 61

3.1. Introduction 61

3.2. Regional Industrial Dominance and Firm Performance 61

3.2.1. Risk-Taking 62

3.2.2. Specialized Inputs 64

3.2.3. Capital 65

3.3. Empirical Research 66

3.4. Conceptual Diagram 71

4. Modeling Framework 74

4.1. Introduction 74

4.2. Productivity Research Designs 74

4.2.1. Aggregate Production Functions 75

4.2.2. Micro-Level Production Functions 82

4.2.3. Changes in Productivity Over Time 84

4.2.4. Production Frontiers 88

4.3. Functional Forms 89

4.4. Overview of Research Design 94

4.5. Production Model 95

4.6. Regularity Conditions 99

4.7. Endogeneity Concerns 101

4.8. Summary 105

5. Concepts, Variables, and Data Sources 106

5.1. Introduction 106

5.2. The *Longitudinal Research Database* 106

5.3. Selection of Study Industries 109

5.4. Regions 113

5.5. Output and Standard Inputs 114

5.6. Regional Industrial Dominance 118

5.7. Agglomeration Economies 125

5.8. Controls 134

5.9. Full Model Equations 137

5.10. Additional Validity Concerns 140

5.11. Summary 146

6. Descriptive Information 147

6.1. Introduction 147

6.2. Estimation Samples 147

6.3. Variable Characteristics 152

6.4. Variable Correlations 160

6.5. Summary 166

7. Dominance, Agglomeration, and Productivity 169

7.1. Introduction 169

7.2. Model Tests and Functional Restrictions 170

7.3. Modeling Results 176

7.3.1. Production Function Regularity Conditions 177

7.3.2. Returns to Scale 179

7.3.3. Standard Inputs and Control Variables 181

7.3.4. Regional Industrial Dominance 189

7.3.5. Agglomeration Economies 198

7.3.6. Dominance-Agglomeration Interactions 203

7.4. Alternative Measures of Regional Industrial Dominance 207

7.5. Regional Dominance versus Industry Scale 216

7.6. Summary 219

8. Extensions: Distance Decay, Region-Wide Dominance, and Plant Size 223

8.1. Introduction 223

8.2. Extension One: Alternative Distance Decay Specifications 224

8.3. Extension Two: Economy-Wide Dominance Controls 233

8.4. Extension Three: Plant Size Interactions 242

9. Summary and Implications....256

9.1. Study Summary and Principal Findings....256

9.2. Research Contributions....260

9.3. Implications for Regional Development Policy....262

9.4. Future Research Directions....265

Appendices....268

1. Derivation of Factor Share Equations and Production System....268

2. Calculation of Monotonicity and Convexity Regularity Criteria....271

3. 1990 Labor Market Areas....272

4. Occupational Data for Labor Pooling....273

5. SIC and Input-Output Codes for Supply Pooling....276

6. Patents and Technology Classes....279

7. Heteroskedasticity-Corrected Versions of Primary Model Results....282

8. Marginal Impacts of Alternative Regional Industrial Dominance Indicators Across Ranges of Standard Inputs and Agglomeration Economies....288

9. Alternative Agglomeration Economy Spatial Decay Profiles....295

10. Economy-Wide Dominance....299

11. Plant Size Interactions....304

References....323

LIST OF TABLES

Table 5.1. Study Industry Definitions by SIC and NAICS Codes 113

Table 5.2. Measures of Regional Industrial Dominance 124

Table 5.3. Production Function Variables 138

Table 6.1. Characteristics of Study Samples 150

Table 6.2. Input and Output Variables: Descriptive Information 154

Table 6.3. Dominance and Agglomeration Economy Variables: Descriptive Information 158

Table 6.4. Control Variables: Descriptive Information 159

Table 6.5. Pearson Pairwise Correlation Coefficients Among Agglomeration Variables 161

Table 6.6. Pearson Correlation Coefficients Between Dominance and Industry Scale Measures 164

Table 6.7. Pearson Pairwise Correlation Coefficients Among Dominance Measures 165

Table 6.8. Pearson Correlation Coefficients Between Agglomeration Variables and Urban and Industry Scale 167

Table 7.1. Tests of Model Restrictions 174

Table 7.2. Regularity Conditions and Returns to Scale 178

Table 7.3. Variables and Coefficients in Translog Production Function Model 179

Table 7.4. Parameter Estimates for Rubber and Plastics (SIC 30) 183-184

Table 7.5. Parameter Estimates for Metalworking Machinery (SIC 354) 185-186

Table 7.6. Parameter Estimates for Measuring and Controlling Devices SIC (382) 187-188

Table 7.7. Parameter Estimates for Alternative Measures of Regional Industrial Dominance 209

Table 7.8. Marginal Impacts of Alternative Dominance Indicators 211

Table 8.1. Alternative Agglomeration Economy Spatial Decay Profiles for Rubber and Plastics (SIC 30) 228

Table 8.2. Alternative Agglomeration Economy Spatial Decay Profiles for Metalworking Machinery (SIC 354) 229

Table 8.3. Alternative Agglomeration Economy Spatial Decay Profiles for Measuring and Controlling Devices (SIC 382)................................230

Table 8.4. Pearson Correlation Coefficients Between Regional Industrial Dominance and Region-Wide Dominance Variables.............................236

Table 8.5. Marginal Impacts of Regional Industry and Economy-Wide Dominance 239

Table 8.6. Sample Descriptive Information for Absolute and Relative Size Classifications 247

Table 8.7. Significance of Marginal Impacts Including Plant Size Interactions for Rubber and Plastics (SIC 30) 250

Table 8.8. Significance of Marginal Impacts Including Plant Size Interactions for Metalworking Machinery (SIC 354) 251

Table 8.9. Significance of Marginal Impacts Including Plant Size Interactions for Measuring and Controlling Devices (SIC 382).............252

Table A.4.1. Study Industry Definitions by SIC and 4-Digit NAICS Codes 273

Table A.4.2. Census Occupational Codes and Study Industry Employment 275

Table A.5.1. Input-Output Codes for Study Industries...277

Table A.5.2. Input-Output Codes for Manufacturing and Producer Services 278

Table A.6.1. Industries Cited in Patents and Relative Importance (Citation Frequency) 279

Table A.6.2. Patent Technology Classes 279-281

Table A.7.1. Parameter Estimates for Rubber and Plastics (SIC 30) with Heteroskedasticity-Corrected Standard Errors 282-283

Table A.7.2. Parameter Estimates for Metalworking Machinery (SIC 354) with Heteroskedasticity-Corrected Standard Errors 284-285

Table A.7.3. Parameter Estimates for Measuring and Controlling Devices (SIC 382) with Heteroskedasticity-Corrected Standard Errors 286-287

Table A.9.1. Alternative Agglomeration Economy Variables for Rubber and Plastics (SIC 30): Descriptive Information 296

Table A.9.2. Alternative Agglomeration Economy Variables for Metalworking Machinery (SIC 354): Descriptive Information 297

Table A.9.3. Alternative Agglomeration Economy Variables for Measuring and Controlling Devices (SIC 382): Descriptive Information 298

Table A.10.1. Economy-Wide Dominance Variables: Descriptive Information 300

Table A.10.2. Parameter Estimates with Economy-Wide Dominance Controls for Rubber and Plastics (SIC 30) 301

Table A.10.3. Parameter Estimates with Economy-Wide Dominance Controls for Metalworking Machinery (SIC 354) 302

Table A.10.4. Parameter Estimates with Economy-Wide Dominance Controls for Measuring and Controlling Devices (SIC 382) 303

Table A.11.1. Marginal Impacts Including Plant Size Interactions for Rubber and Plastics (SIC 30), 1992 305-306

Table A.11.2. Marginal Impacts Including Plant Size Interactions for Rubber and Plastics (SIC 30), 1997 307-308

Table A.11.3. Marginal Impacts Including Plant Size Interactions for Rubber and Plastics (SIC 30), 2002 309-310

Table A.11.4. Marginal Impacts Including Plant Size Interactions for Metalworking Machinery (SIC 354), 1992 311-312

Table A.11.5. Marginal Impacts Including Plant Size Interactions for Metalworking Machinery (SIC 354), 1997 313-314

Table A.11.6. Marginal Impacts Including Plant Size Interactions for Metalworking Machinery (SIC 354), 2002 315-316

Table A.11.7. Marginal Impacts Including Plant Size Interactions for Measuring and Controlling Devices (SIC 382), 1992 317-318

Table A.11.8. Marginal Impacts Including Plant Size Interactions for Measuring and Controlling Devices (SIC 382), 1997................ 319-320

Table A.11.9. Marginal Impacts Including Plant Size Interactions for Measuring and Controlling Devices (SIC 382), 2002................ 321-322

LIST OF FIGURES

Figure 3.1. The Context of Firm Performance 72

Figure 5.1. Alternative Spatial Decay Profiles 129

Figure 7.1. Marginal Impacts of Regional Industrial Dominance by Level of Dominance 194

Figure 7.2. Marginal Impacts of Regional Industrial Dominance Across Range of Standard Inputs 197

Figure 7.3. Marginal Impacts of Regional Industrial Dominance Across Range of Agglomeration Economies 205

Figure 7.4. Marginal Impacts of Alternative Regional Industrial Dominance Indicators Across Levels of Inputs and Agglomeration Economies for Rubber and Plastics (SIC 30), 1992 215

Figure A.3.1. 1990 Labor Market Areas 272

Figure A.8.1. Marginal Impacts of Herfindahl-Hirschman Regional Industrial Dominance Across Range of Standard Inputs 289

Figure A.8.2. Marginal Impacts of Rosenbluth Regional Industrial Dominance Across Range of Standard Inputs 290

Figure A.8.3. Marginal Impacts of Gini Regional Industrial Dominance Across Range of Standard Inputs 291

Figure A.8.4. Marginal Impacts of Herfindahl-Hirschman Regional Industrial Dominance Across Range of Agglomeration Economies 292

Figure A.8.5. Marginal Impacts of Rosenbluth Regional Industrial Dominance Across Range of Agglomeration Economies 293

Figure A.8.6. Marginal Impacts of Gini Regional Industrial Dominance Across Range of Agglomeration Economies 294

CHAPTER ONE: INTRODUCTION

1.1. Overview

The relationship between industrial structure and economic performance has long been of interest to researchers in regional science, business and industrial organization, and economics, as well as to government officials and practitioners of economic development planning. A highly influential article published by Benjamin Chinitz in 1961 focused attention on the effects that industry size, structure, and economic diversification have on firm performance and regional economic health. The article also implies a related but conceptually distinct issue that has been largely overlooked since: the influence that regional concentration within a specific industry has upon smaller local establishments in that industry.

Chinitz suggests that regional concentration may act through input prices, capital accessibility, labor sharing or pooling, and the conduct of entrepreneurial activity, to reduce the regional availability of agglomeration economies and ultimately diminish economic performance. For instance, major corporate players may set labor market conditions with respect to wage rates, benefits, bargaining, and employment stability, such that smaller firms have difficulty attracting and retaining skilled workers. Regional lenders accustomed to serving large companies may be less inclined to serve smaller, more entrepreneurial, and higher risk businesses. Local and state government agencies, as well as universities and community colleges, may be more responsive to the needs of dominant firms, thereby tilting key institutional and policy conditions toward larger, established businesses and away from smaller competitors.

This study investigates two interrelated research questions. The first is whether manufacturing plants in regions and industries that are dominated by a few relatively large businesses are less productive, other things being equal, than establishments in the same industries that are located in regions characterized by a broader firm size distribution. The second, more specific, hypothesis postulates that small establishments in dominated regional industries are less productive because they are limited in their ability to capture regional agglomeration benefits and thus face rigidities in deploying and adjusting production factors to maximum advantage.

The research is performed using the confidential *Longitudinal Research Database* (LRD) of the United States Census Bureau. Establishment information from the LRD is combined with data from publicly available sources to create indicators of regional industrial dominance and potential agglomeration economies, along with relevant controls. A cross-sectional establishment-level production function is estimated jointly with its associated factor share equations for several industries to model explicitly the influence of regional industrial dominance on business performance. The use of establishment-level data avoids many of the theoretical and methodological pitfalls encountered in earlier studies of agglomeration and productivity. In addition, the study explicitly examines the geographic dimension of interfirm relationships by incorporating spatially attenuating measures of potential agglomeration economies.

1.2. Research Significance

This research contributes directly to the literature on regional diversity, agglomeration, business concentration, and industrial structure. It does so by investigating a heretofore understudied aspect of industrial structure—the influence of industrial dominance at the regional level on establishment performance—and illuminating key interrelationships among regional industrial dominance, agglomeration economies, and the other characteristics of regions and establishments that determine economic performance at the plant, industry, and regional levels. The estimation results provide insight into the factors that determine the ability of relatively small establishments to take advantage of productivity-enhancing local external economies.

The dissertation extends the regional science literature by focusing on the intra-industry aspects of industrial organization, by examining industrial structure using a productivity framework, and by considering explicit measures of the sources of agglomeration economies that reveal the spatial scale of different interfirm effects. Indeed, the topic aims squarely at two subjects recently identified as central to the current development of regional science: the role of agglomeration in economic growth, and the spatial extent of localized agglomeration externalities (McCann and Shefer 2005). The results add to the growing body of work that models productivity at the establishment level, doing so with a nationwide dataset. Finally, the analysis helps develop a clearer picture of the extent of regional industrial dominance in selected manufacturing industries across the United States, providing a baseline for future work on the topic.

1.3. Policy Significance

The central aim of economic development practice is to create a regional economic environment that is nurturing to local businesses and conducive to highly productive economic activity. Accordingly, local access to valuable inputs such as inexpensive and/or specialized labor, intermediate suppliers, financial capital, and industry-relevant information is crucial to long-term sustainable regional economic progress. Despite a long history of academic research concerning the regional context of industrial activity, the specific relationships that join localized business resources with firm performance are not well understood. The largely unexplored area of the interaction of regional industrial structure with agglomeration economies carries substantial implications for the design of economic development policy. Without concrete and detailed knowledge of the effects that industrial dominance has on firms' use of localized inputs and their resulting economic performance, policy makers lack the information necessary to develop effective policy instruments to address issues related to regional industrial structure and input accessibility.

Chinitz suggests that a concentrated regional corporate structure may limit business adaptability and performance. In particular, the hypotheses examined in this dissertation argue that regional industrial dominance may act as a limiting factor on the ability of local firms to deploy and adjust workforce, capital, and other factors of production to maximum advantage and to engage in entrepreneurship. Because small business growth and entrepreneurial activity are vital for regional adaptability and economic restructuring, industrial concentration may be a crucial determinant of regional adjustment capacity (Audretsch 2001; Acs and Varga 2005). In effect, industrial dominance may be a specific mechanism by which regions and businesses "lock-in" to a particular set of industrial competencies. As markets evolve and technology changes, those competencies—once key regional economic engines—eventually may become economic liabilities (Arthur 1989; Grabher 1993; Bergman 2002; Martin and Sunley 2006). Conversely, negative lock-in effects might be minimized or avoided to the degree that adjustment via new business growth and entrepreneurial activity are maximized. In other words, industrial dominance may be linked with economic adjustment rigidity at the regional scale. Although this research is conducted at the level of the establishment, regional industrial dominance is viewed as a key influence on regional-level outcomes.

The study is particularly relevant to economic development policy in the context of the recession of the early 2000s and the subsequent jobless recovery and industrial restructuring in many areas of the United States. American regions continue to face major workforce dislocation as labor-intensive industries migrate to Asia, Latin America, and other low-cost locations. Numerous smaller regions, such as "one-company towns", must remake themselves entirely in the face of heightened global competition. At both the regional and national levels, increasing business concentration in many sectors in the United States may have serious implications for the capacity of regions to adjust to new economic conditions promptly and with a minimum of worker dislocation. To address these challenges, local policymakers require a better understanding of regional capacity to adapt to national and global economic shifts. It is hoped that the findings of this study will prove useful to both practitioners and researchers interested in understanding the features of establishments and industries that either enhance or limit the capacities of regional economies to adjust continually to changing markets, demand, tastes, and technology.

1.4. Organization

The next chapter of this dissertation begins by defining regional industrial dominance. The bulk of the chapter then focuses on reviewing two bodies of theoretical and empirical literature that constitute the essential background for the subject: firm size distributions and regional agglomeration. Chapter Three presents the conceptual framework guiding the study, describing the relationships hypothesized to exist among regional industrial dominance, agglomeration economies, and establishment productivity. Following a discussion of the main research designs that have been developed to investigate economic productivity, Chapter Four describes the model and statistical methodology used in the analysis. The data sources and variables are detailed in Chapter Five, along with related measurement issues. Chapter Six contains descriptive analyses of the samples and model variables. The heart of the dissertation is Chapter Seven, which presents and analyzes the principal modeling results, and Chapter Eight reports on three extensions of the primary modeling strategy. Chapter Nine concludes by summarizing the main findings of the study, discussing the implications for research and policy, and suggesting possible areas for future research concerning regional industrial dominance.

CHAPTER TWO: REGIONAL INDUSTRIAL DOMINANCE, INDUSTRIAL ORGANIZATION, AND AGGLOMERATION

2.1. Introduction

As suggested by the designation "regional industrial dominance", the concept at the heart of this dissertation is defined with reference to characteristics of both regions and industries. As such, the appropriate background for the research draws from understandings both of industrial structure and of the functional characteristics of economies at the regional scale. This presents a substantial challenge in that research efforts in the fields of industrial organization and regional economics mainly have been conducted separately from each other. The ambition in this chapter is to bring together the theory and empirical work from both bodies of research that is relevant to the investigation of regional industrial dominance.

Each of the two areas of scholarship—industrial organization and regional economics—is immense, ample for years of pure reading and classification labors. No attempt is made here to describe or provide an overview of the large amount of research in subjects such as competitive market operation, production strategies, business performance, and regional innovation systems that touch only peripherally on the topic of regional industrial dominance. The chapter concentrates instead on the portions of the fields of industrial organization and regional economics directly relevant to the issues of the regional organization of industries and localized external factors determining business performance that are central to this study.

After introducing the concept of regional industrial dominance, this chapter reviews the two topics that form the most appropriate theoretical foundation for this research. The first, drawn primarily from the industrial organization literature, concerns regularities in firm or establishment size distributions. The second, regional agglomeration, is the theoretical backing employed by Chinitz. These two threads form the main underpinnings of the empirical analyses designed and conducted in Chapters Three through Eight. Two works that constitute key antecedents to this study are described in particular detail.

2.2. The Concept of Regional Industrial Dominance

Urban economist Benjamin Chinitz has long emphasized supply-side issues in regional economics (for interpretations and discussions of Chinitz's ideas, see, for example, Carlino 1980; Malamud 1987; Netzer 1992; Norton 1992). In his seminal article in the *American Economic Review* (1961), Chinitz discusses several interesting and important issues surrounding regional industrial structure, including the effects that one industry's size has on factor prices in other regional industries, the ways in which non-diversified economies differ from diversified economies as locations for industrial development, and how overall economic structure impacts the regional availability of business services and other inputs. These topics have since received considerable attention in various segments of the literature. In particular, there is quite a large literature on the impacts of industrial diversity, and the body of research that examines the relationship between the regional establishment size distribution and growth is substantial as well (see sections 2.3 and 3.3).

Yet Chinitz's article also suggests a related but conceptually distinct question: how does regional industrial dominance—the extent to which the activity of an industry within a particular region is concentrated in a single firm or small number of firms—influence the competitive performance of other local firms within that industry? Chinitz suggests that the influence of industrial concentration in general may act through input prices, financing or capital availability, labor sharing or pooling, and entrepreneurial activity. He also proposes that industrial concentration may influence the regional availability of agglomeration economies.

Little theoretical or empirical work has been conducted directly on the particular issue of intra-industry domination. Debates on the significance of the Chinitz paper have focused on industrial diversity or the regional firm size distribution (Evans 1986; Carlino 1987; Norton 1992). Although their study has yielded important implications, the concepts of industrial diversity and the firm size distribution are not by themselves sufficient to adequately test the domination hypothesis. Industrial diversity pertains to sectoral mix (the combination of economic activities in a region) rather than industrial structure, and both concepts indicate corporate domination only in aggregate terms. The distinct issue of regional industrial dominance may be crucial for understanding the dynamics of regional economies in the vast majority of regions that neither experience overriding economic dominance by a single firm or industry nor have approximately competitive markets in each industry.

2.3. Firm and Establishment Size Distributions

Industrial organization and strategy would seem to be a logical discipline within which to seek prospects and guidance for examining the issue of regional industrial dominance. The literature concerning industrial organization, competitive market operation, production strategies, and business performance is immense and varied, but the vast majority does not consider the issues of industrial structure and external factors determining business performance at the regional scale. The line of inquiry that most closely relates to the research topic of regional industrial dominance centers around the postulate termed Gibrat's Law.

In 1931, French economist Robert Gibrat observed that the national distribution of the size of manufacturing plants was highly skewed. His initial interest in examining the empirical plant size distribution in French manufacturing was motivated by evidence of certain skew patterns arising with some frequency in non-economic fields such as biology and astronomy (Sutton 1997a). In fact, mathematically-related skew distributions such as the Yule and Pareto distributions appear in a wide range of diverse biological, social, and geographic settings, from the rank-ordering of city populations to the number of species per genus to the frequencies of words appearing in prose (Simon 1955; Ijiri and Simon 1977; Ioannides and Overman 2003; Cordoba 2008).[1] The skew nature of firm sizes has

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[1] The Yule distribution, sometimes termed the Yule-Simon distribution, is discrete with probability mass function

$$f(k,\theta) = \theta \int_0^1 y^{k-1}(1-y)^{\theta} dy$$

where k is an integer greater than or equal to one and θ is positive. The Yule distribution has the property that for large values of k,

$$f(k,\theta) \propto \frac{1}{k^{\theta+1}},$$

so that the tail of the distribution follows Zipf's law: the relative frequency of the k^{th} largest size category is inversely proportional to a power of k. The Pareto distribution, also known as the Bradford distribution, been observed to be robust across industrialized nations, over time, and for different definitions of size (Collins and Preston 1961; Ijiri and Simon 1977; Stanley *et al.* 1995; Axtell 2001).

The surprising commonness of particular skew distributions has led researchers to seek broad theoretical mechanisms that may apply across the genera of observed phenomena (Ijiri and Simon 1977; Caves 1998; Audretsch 2001). The dynamics of entry and exit present one such mechanism that applies well to a variety of economic as well as non-economic phenomena. Gibrat suggested that the pattern of French manufacturing plant sizes might be explained by firm growth rates being independent of the firm size already attained, the proposition that has been known since as Gibrat's Law of Proportional Effect (Sutton 1997a).

Since Gibrat's initial foray, the subject of the firm size distribution has received less attention than many other more prominent topics in industrial organization, in part because a thorough investigation requires a hefty amount of data available at a disaggregate level (Sutton 1997a; Gans and Quiggin 2003).[2] Nevertheless, a considerable volume of work has offered, refined, and tested theoretical models designed to explain the observed skewed distribution of firm sizes, as well as related dynamic

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is a continuous analog of Zipf's law that approximates the tail of the Yule distribution. The Pareto distribution has probability mass function

$$f(x,\alpha,\beta)=\alpha\frac{\beta^{\alpha}}{x^{\alpha+1}}$$

where α and β are parameters and x is greater than or equal to β. See Simon (1955), Ijiri and Simon (1977), and Fujiwara *et al*. (2004) for more details on the Yule, Zipf (zeta), and Pareto distributions. Bottazzi and Secchi (2003a) and de Wit (2005) discuss alternative skew distributions.

[2] Some studies have used aggregated data, but their conclusions are subject to possible aggregation bias (Bottazzi and Secchi 2003a; Fagiolo and Luzzi 2006).

measures such as relative concentration, turnover, and rank mobility (for reviews, see Sutton 1997a; Caves 1998; Audretsch *et al.* 2004).

Despite the obvious link (via aggregation) between firm behavior and industry-level (or regional) structure, the literature has for the most part approached the size distribution of firms and industries separately. This partition has some empirical justification: phenomena that evidence regularities across industries, such as turbulence in market shares, often have quite distinct behaviors at different scales or levels of aggregation (Davies and Geroski 1997; Bottazzi *et al.* 2007). In addition, firm size distributions are nearly always considered aspatially within the industrial organization literature, with firms or plants classified by industry or sector irrespective of geographic location.

At the firm level, the Gibrat proposition has generally been upheld only for a particular subset of firms: those that not only survive an initial period subsequent to market entrance but that also attain sufficient size within the initial period to achieve minimum efficient scale for production (Becchetti and Trovato 2002). Studies examining large incumbent firms in developed nations report support for Gibrat's Law (Simon and Bonini 1958; Hymer and Pashigian 1962; Hall 1987; Axtell 2001; Bottazzi and Secchi 2003b; Geroski *et al.* 2003; Fujiwara *et al.* 2004; Bottazzi and Secchi 2005; 2006; Goddard *et al.* 2006; Bottazzi *et al.* 2007; Gupta *et al.* 2007), whereas myriad investigations of broader cross-sections of firms consistently find newer and smaller firms to grow faster than Gibrat's Law would predict and also to suffer from higher mortality rates (Evans 1987a; 1987b; Hall 1987; Schmalensee 1989; Dunne and Hughes 1994; Mata 1994; Hart and Oulton 1996; Sutton 1997a; Harhoff *et al.* 1998; Dinopoulos and Thompson 1999; Almus and Nerlinger 2000; Audretsch 2001; Hart and Oulton 2001; Lotti *et al.* 2001; Goddard *et al.* 2002; Hamilton *et al.* 2002; Correa Rodriguez *et al.* 2003; Lotti *et al.* 2003; Rodriguez *et al.* 2003; Esteve-Perez *et al.* 2004; Lotti and Santarelli 2004; Persson 2004; Bartelsman *et al.* 2005; Cefis and Marsili 2005a; 2005b; Harris and Trainor 2005; Taymaz 2005; Ushijima 2005; Yasuda 2005; Calvo 2006; Rossi-Hansberg and Wright 2006; Cabral 2007; Lotti 2007; Moreno and Casillas 2007; Rufin 2007; Strotmann 2007; Petrunia 2008; Box forthcoming).[3,4] Numerous models of firm entry, survival, growth, and exit behavior have been proffered in the industrial organization literature to explain these observed dynamics.

When examined at the industry scale, idiosyncratic or sector-specific mechanisms tend to dominate firm size distributions, particularly for smaller industries or sectors, suggesting that it is not possible to capture the range of observed empirical regularities in a single model or even a single type of model (Schmalensee 1989; Sutton 1997a; 1997b; Audretsch *et al.* 2004; de Wit 2005).[5] In the Netherlands, Marsili's (2005; 2006) analyses suggest that industry-level departures from Gibrat's Law in manufacturing might be related to the technological or innovation regime of the industry, though no

[3] Although Bottazzi *et al*. (2001) reject Gibrat's Law for the world's largest pharmaceutical firms, subsequent studies performed on essentially the same sample (Bottazzi and Secchi 2005; 2006) as well as on different samples of pharmaceuticals firms (De Fabritiis *et al.* 2003; Buldyrev *et al.* 2007; Pammolli *et al.* 2007) either uphold the proposition or explain observed deviations in terms of behavior regarding industrial submarkets. Cefis *et al*. (2007) also reject Gibrat's Law for pharmaceutical companies, finding that growth rates differ systematically but seemingly not on the basis of firm size.

[4] Firms in developing or transitional parts of the world may not follow the same patterns as those in developed nations. For example, Bigsten and Gebreeyesus (2007) report that small Ethiopian firms grow faster than larger firms in both manufacturing and services, but in a study of nine sub-Saharan African nations Van Biesebroeck (2005) finds that large manufacturers experience greater average growth rates than small companies. Siebertova and Senaj (2007) demonstrate a negative association between firm size and growth rate in Slovakia, but note that another recent study of that country found no relationship.

[5] This is true despite the logical necessity that there be substantial regularities across industries in order for them to aggregate to the whole economy (Ijiri and Simon 1977, p. 19).

clear rule can be established. In the aggregate, the services display much the same characteristics as the manufacturing sector (Lotti 2007), yet Audretsch *et al.* (2004) find that hospitality services industries follow Gibrat's Law much more closely, perhaps due to lesser survival bias in the industry. Substantial differences across industries have been uncovered in many other nations as well, with no consistent explanation sufficing for the disparities (Tybout 2000; Bottazzi *et al.* 2002; Lotti and Santarelli 2004; Reichstein and Jensen 2005; Bottazzi *et al.* 2007). The skewness of firm sizes in individual industries may result to some degree from industry-specific processes such as economies of scope; another possibility is that the underlying processes yield multiple viable equilibria (Sutton 1997a; 1997b). The particular form of an industry's firm size distribution may even change over time while retaining its essential skewness (Cabral and Mata 2003; Gatti *et al.* 2004; Bertinelli *et al.* 2006; Marsili 2006).

There is an additional major impediment to modeling industry-level firm size distributions. Suggesting a precise distribution falls into the class of what are termed by Ijiri and Simon to be "extreme hypotheses," with regard to which standard inferential statistics are not appropriate (1977, p. 109). Extreme hypotheses are those which seek to match a particular distribution to a phenomenon rather than support a weaker statement of general relationship. Because inferential statistics cannot differentiate incorrect extreme hypotheses from inaccuracies arising from the inherent simplification represented by the distributional form, they give little aid in distinguishing invalid generalizations from those that are simply approximate (Ijiri and Simon 1977, pp. 113-

114, 155).[6] Extreme hypotheses are not subject to explicit confirmation or falsification, but only to a process of testing and refining (and perhaps rejecting) through the analysis of mechanisms capable of producing the generalization (Ijiri and Simon 1977, pp. 122-123; Powell 2003).

One way to avoid the problems of extreme hypotheses is to measure firm size distributions with simple indicators rather than fully defined distributions (Needham 1978; Hay and Morris 1991). This tactic has several drawbacks. Summary statistics contain less information than a full distribution, and their use may mask pertinent information (Golan *et al.* 1996). There are numerous possible indicators, possessing different properties, with no general agreement upon which are the best or most useful (Amato 1995).[7] Furthermore, fitting a distribution is ultimately more useful than employing simple unitary indicators if the distribution may be demonstrated to have a theoretical as well as empirical basis, thus allowing for causal modeling and more direct analysis of policy implications (Ijiri and Simon 1977, pp. 13, 150).

Despite the inherent deficits of the strategy, summary statistics are regularly substituted for the full specification of the firm size distribution in industrial organization studies (examples include Martin 1979; Shepherd 1982; Attaran and Saghafi 1988; Kambhampati 1998; Robinson and McDougall 1998; Robinson 1999; Kelly and Gosman 2000; Pryor 2001; Bottazzi *et al.* 2007). Measures of concentration based on size traits such as employment or sales have been examined extensively in relation to industry-level profit rates, with early research finding that more concentrated industries tend to earn

[6] Ijiri and Simon note that with large enough samples, statistical tests will always reject hypotheses of theoretical distributions because the distributions are "approximate theories that do not capture the fine structure of phenomena" (1977, p. 4).
[7] Several of the most commonly employed measures of industrial structure are described in detail in Section 5.6.

higher profit rates (e.g., Bain 1951; Bradburd and Over 1982). More recent studies have found the reverse generally to be true once market share is included as a control and have suggested a much more complex relationship between market power, efficiency, and performance (Ravenscraft 1983; Kwoka and Ravenscraft 1986; Hay and Morris 1991; Amato 1995; Bennenbroek and Harris 1995; Berger 1995; Azzam 1997; Bajtelsmit and Bouzouita 1998; Berger and Hannan 1998; Mueller and Raunig 1999; Azzam and Rosenbaum 2001; Choi and Weiss 2005; Kambhampati and McCann 2007; see reviews in Schmalensee 1989; Amato and Wilder 1995; Azzam *et al.* 1996; Cool and Henderson 1998; Fourie and Smith 1998; 1999).

Industrial concentration has also been linked to productivity, changes in productivity over time, and innovation intensity. Empirical studies in several nations reveal that industrial concentration has a curvilinear relationship with technical production efficiency, wherein increases in concentration lead to greater productivity up to a point, beyond which further concentration decreases productivity (Caves and Barton 1990; Green and Mayes 1991; Caves 1992; Nickell 1996; Gumbau-Albert and Maudos 2002). In Japan, output growth and industrial concentration are positively related (Cortes 1998), but productivity in R&D-performing manufacturing firms is lower in industries with larger aggregate price-cost margins (an indicator of market power) (Okada 2005). Concentration yields lower productivity growth in manufacturing companies in the United Kingdom (Nickell 1996; Nickell *et al.* 1997). Gopinath *et al*. (2004) find that increases in concentration in U.S. manufacturing industries have an inverted-U-shaped relationship with the growth rate of productivity similar to that found for production efficiency. More concentrated U.S. industries obtain smaller marginal productivity benefits from information technology (Melville *et al.* 2007). Although early studies indicate a similar nonlinear inverted-U association between industrial concentration and the intensity of research and development (R&D) activity (the first such analysis being Scherer 1967), the consensus in the literature is that the causal relationship is bidirectional (i.e., rapid innovation also leads to industrial concentration) and depends on industry characteristics (Scherer 1980; Cohen and Levin 1989; Vossen 1999; Bhattacharya and Bloch 2004; Rogers 2004). Moreover, the intensity of R&D efforts expended is not necessarily correlated with the innovative output rate achieved.

The properties of extreme hypotheses and the empirical differences observed across industries help to explain why the main thrust of research around Gibrat's Law has treated the distribution of firm or plant sizes as an empirical outcome and focused on the task of uncovering and elucidating possible underlying causal mechanisms (Sutton 1997a).[8] In contrast, the segment of regional science and economics that has examined the sizes of firms or plants has most often approached the size distribution as a regional trait that itself affects other regional outcomes of interest, the approach adopted in this research. (The discussion of these findings is postponed to the review of empirical research on establishment size and industrial diversity in section 3.3). Several studies do suggest that industrial concentration is positively related to productivity and productivity growth for low levels of concentration but detracts from productivity at higher concentration levels. Nevertheless, the relationship of industrial concentration to productivity, as well as other outcomes such as profit levels and innovation, is complex and depends on industry-specific characteristics. As a practical consideration, the

[8] This characterization is evident to a much lesser degree with regard to those works utilizing summary statistics.

difficulties encountered in attempting to fit fully-specified firm size distributions at the industry level encourage the careful application of summary statistics in this research. Perhaps the most important conclusion to be drawn for this study from the existing research on firm size distributions is the necessity of pursuing the investigation of regional industrial dominance on the basis of individual industries, as a subject distinct from previous investigations of national or industry-level market power. Regarding the question of how exactly to do so, there is much to be gained from the theory of agglomeration economies.

2.4. Agglomeration Economies

The most suitable theoretical foundation for investigating the effects of regional industrial dominance is that used by Chinitz himself, the theory of agglomeration. Agglomeration is central to the modern understanding of regional development, and the body of research on agglomeration economies is massive and complex, spanning multiple subdisciplines within economics, geography, and regional science. Rather than attempting to encapsulate this enormous literature, this section provides a brief overview of the development of the subject, linking agglomeration theory with industrial structure, and then concentrates on a review of empirical approaches. For more extensive reviews of agglomeration theory, see Malmberg (1996), Feser (1998a), Hanson (2001), Rosenthal and Strange (2004), and Renski (2006).

2.4.1. The Theory of Agglomeration Economies

The earliest basis for postulating that regional industrial context affects firm performance is likely Alfred Marshall's classic analysis of the benefits of firm co-location in specialized industrial districts. Marshall ([1890] 1910) identifies three major sources of external economies arising from regional co-location of similar businesses. The first is improved access to specialized inputs. The larger the local industry, the more feasible and efficient specialization becomes among producers for that industry, and thus the less expensive it becomes for firms in the industry to purchase and utilize specialized inputs in their production processes. Marshall discusses the example of highly specialized machinery that, while not cost-effective to own and operate within a single producing firm, is able to "pay its expenses" if operated for the benefit of many firms ([1890] 1910, IV.x.3, p. 271). The concentration of purchasing power urges local suppliers to cater to the particular needs of the industry.

Second, labor advantages accrue analogously to those concerning material inputs. A spatial grouping of firms with similar or complementary labor needs creates a sizeable local pool of qualified labor, increasing job opportunities for specialized skilled workers and raising the chances of a good match between employer labor demand and employee skill supply. In contrast, an isolated firm "is often put to great shifts for want of some special skilled labour; and a skilled workman, when thrown out of employment in it, has no easy refuge" ([1890] 1910, IV.x.3, pp. 271-2). This benefit extends to associated input producers as well, since larger input markets also allow for a greater division of labor among input-producing firms.

The third Marshallian external economy relates to simplified diffusion or spillover of knowledge and innovations. Locations with many firms engaged in similar production processes have greater potential for information exchange, whether through firm-level interactions, interpersonal communication, or employee job switches, that speeds and improves technological progress. Marshall's famous explanation is that where a particular industry is concentrated, "mysteries of the trade become no mysteries; but are as it were in the air…if one man starts a new idea, it is taken up by others and combined with suggestions of their own; and thus it becomes the source of further new ideas" ([1890] 1910, IV.x.3, p. 271).

Although Marshall's original exposition of the notion of agglomeration economies is more than a century old, his conception has proven remarkably durable. Theoretical work on the subject has concentrated mainly on further clarifying the original three Marshallian sources of externalities (agglomeration economies) and extending the list of possible agglomeration economy sources (Feser 1998a). Many studies adopt the distinction proffered by Hoover (1937) between localization and urbanization economies (see section 2.4.2.2). Hoover defines localization economies as those advantages that accrue to co-located firms within a particular industry, and urbanization economies as the benefits available to all types of firms in a single location. With respect to knowledge spillovers and innovation, Jacobs (1969) stresses that the cross-fertilization of ideas across diverse industries is crucial for regional economic dynamism, and Porter (1990) argues that competitive rivalry within industries improves innovation and performance. These ideas often are termed "Jacobs externalities" and "Porter externalities" in the literature and have been tested repeatedly against Marshall's concept of intra-industry knowledge spillovers (section 2.4.2.3) (Audretsch 2003).[9] Another commonly raised distinction separates static economies (short-term reversible advantages) from dynamic economies (benefits realized in the long run, such as heightened technological learning) (Glaeser *et al.* 1992; Harrison *et al.* 1996; Feser 1998a). Further conceptual divisions of agglomeration economies have been suggested (e.g., Parr 2002a; 2002b; Parr 2004) but for the most part have been inessential to the mainstream of agglomeration economy research.

There is some overlap between the agglomeration economies and industrial organization literatures. Stigler suggested in 1951 that localization economies may provide an organizational alternative to vertically integrated firms; a recent empirical study supports this contention, albeit weakly (Holmes 1999). Subsequent authors have considered as well the advantages of proximity for gaining external economies of scope (multiple goods production) and reducing linkage costs, such as for conducting transactions or entering into collaborative agreements (Scott 1986; 1988b; Pudup 1992; Enright 1995; Renski 2006). In all of these cases, agglomeration economies alter the optimal firm organizational structure, allowing for greater specialization and efficiency.

The "new industrial districts" literature departs from pure agglomeration theory by embracing sociologist Mark Granovetter's (1985) critique of classical and neoclassical economics as "undersocialized", i.e., ignoring the fact that economic relationships occur within social structures and thus are affected by cultural and historical factors.[10] Work in

[9] In this context, Marshall's knowledge spillover agglomeration economy is commonly referred to as the Marshall-Arrow-Romer (MAR) type of externality to credit the influential formalizations of the benefits of knowledge presented by Arrow (1962) and Romer (1986).

[10] Granovetter also criticized institutional economists for "oversocializing" individual behavior, or modeling actors as following the dictates of habit or custom automatically, at the expense of rational choice (1985, p. 485).

this mode emphasizes the "embeddedness" of economic interactions within the social fabric, incorporating theories of social interaction, transaction costs, and trust along with Marshallian agglomeration economies to analyze the organization of production in which proximity advantages accrue to firms from social and institutional as well as economic relationships (Harrison 1992; Feser 1998a; Malmberg and Maskell 2002; Corolleur and Courlet 2003). The Emilia-Romagna region of Italy has become the paradigmatic source for examples of such districts, drawing from Piore and Sabel's (1984) description of a flexible production organization based on small manufacturers that simultaneously compete for business and learn from each other in formal and informal cooperative networks. Given the importance placed on local history and difficult-to-measure social and contextual factors, and the fact that the industrial districts have not become as widespread as envisioned by some proponents, it is not surprising that most research on new industrial districts has been in the form of case studies (Appold 1995; Feser 1998b; Raco 1999; Helmsing 2001; Feser and Sweeney 2002; Essletzbichler 2003; examples include Scott 1988b; Saxenian 1994; Enright 1995; Suarez-Villa and Rama 1996; Coe 2001; Kloosterman and Lambregts 2001; Rantisi 2002; Watts *et al.* 2003; Molina-Morales and Martinez-Fernandez 2004; Mota and de Castro 2004; Muscio 2006).

Aside from these intersections, most industrial organization research concentrates on national or industry-specific structural attributes, whereas agglomeration economies work focuses specifically on the conditions constituting the regional economic environment. Conceptually, the topic of regional industrial dominance is situated in the juncture, defined with reference to both localized environmental conditions and industrial structure. Agglomeration theory nevertheless provides a suitable and logical framework for studying regional industrial structure. The theories of localization economies and new industrial districts presented above cross the disciplinary boundary successfully, demonstrating that agglomeration theory is effective in explaining regional- and firm-level organization and behavior. The acknowledged importance of local and situational factors, however, suggests that to achieve the fullest possible understanding of the operation and implications of regional industrial dominance it may be necessary to implement more than one research strategy.[11] This study concentrates on one approach, employing the theory of agglomeration economies to develop large-sample quantitative analyses of the effects of regional industrial dominance.

2.4.2. Empirical Studies of Regional Agglomeration Economies

There is an extensive body of research that investigates the agglomeration economies generated by the regional proximity of like as well as dissimilar firms. Because external economies cannot be measured directly, empirical analyses instead estimate potential agglomeration economies based on observable characteristics (Richardson 1974a). Overall, quantitative research in the area has been substantially encumbered by persistent methodological impediments and poor quality data. One frank assessment asserts that empirical research has not managed to keep up with theoretical developments in the subject (David 1999). Yet work on the subject continues unabated,

[11] This dissertation is part of a larger research project funded by the National Science Foundation that employs multiple research design strategies. This micro-level productivity analysis is one aspect; the project also includes case study research concerning the same basic questions. The purpose of conducting case studies is to explore the contextual issues that affect the relationships between corporate dominance, agglomeration economies, and productivity in more depth and detail than is possible through formal productivity analysis. The quantitative modeling approach taken in this dissertation maximizes external validity, whereas case studies permit greater internal validity in investigating complex institutional and contextual factors at the obvious expense of generalizability (Yin 1994). To the degree that the findings are consistent, the combination of this analysis with the complementary case studies will yield more robust conclusions.

and the accumulation of results yields interesting regularities that provide direction to continuing research efforts. Recent approaches, in particular those using data at the establishment level, hold substantial promise.

2.4.2.1. Size, Density, and Productivity

The most frequently adopted empirical approach to studying agglomeration is to examine productivity across a range of business environments, relating differences in measured or estimated performance to indicators of local or regional agglomeration economies (Moomaw 1983a; Malamud 1987; Glaeser *et al.* 1992; Gerking 1994; Aji 1995; Malmberg 1996; Rosenthal and Strange 2004). By modeling a production function that relates output levels to standard production inputs and other factors of interest, the effects of external economies may be measured with shift parameters. As a simplifying assumption, most studies specify the parameters as Hicks-neutral.[12] Through the early 1990s or so, secondary data were all but unavailable at the firm level, forcing empirical analyses to make use of regional or industry measures despite the potential bias introduced by insufficiently disaggregate variables. In addition, because even aggregate capital information is not readily available, many researchers have had to introduce convoluted econometric strategies to replace the capital input in productivity models. More recently, analyses have made use of data at the establishment level to avoid these limitations (see section 2.4.2.5; see also sections 4.2.1 and 4.2.2 for further discussion of methodological issues in productivity studies).

[12] A Hicks-neutral shift does not alter the levels of use of standard inputs relative to one another. Factor-augmenting terms, in contrast, allow the ratios of standard inputs into production to change. See section 4.2.1.

City or regional size was used to indicate agglomeration economies in early productivity-based studies, with population found to be positively related to labor or total productivity (Aberg 1973; Sveikauskas 1975; Segal 1976; Fogarty and Garofalo 1978; Moomaw 1981b). Population density has commonly been substituted for size as a proxy for agglomeration economies, revealing a similar positive association with production or productivity that holds across a range of industrialized nations (e.g., Richardson 1974b; Nicholson 1978; Tabuchi 1986; Ciccone and Hall 1996; Ciccone 2002). Seeking an explanation for industrial deconcentration observed in the 1960s and 1970s, Moomaw (1985) presents evidence that the manufacturing productivity advantage of urban areas declined from 1967 to 1977, positing as a possible cause advances in technology and telecommunications that reduced distance costs. Beeson (1987a) unexpectedly finds U.S. states with greater metropolitan population shares to have *lower* productivity growth, but this effect is offset by productivity gains for states containing one of the largest 20 metropolitan areas. Similarly, Beeson and Husted (1989) discover metropolitan population shares to be associated with greater state-level productive efficiency, but larger metropolitan populations with lower productivity. A simultaneous equations approach incorporating labor demand and supply yields evidence of agglomeration economies for U.S. metropolitan areas of up to two million residents (Calem and Carlino 1991). Carlino and Voith (1992) report that states with greater percentages of their population located in metropolitan areas have greater productivity, though a quadratic term representing congestion disamenities offsets the effect for relatively high levels of urbanization. Metropolitan or urban counties are more productive than rural locations for meat packing and household furniture manufacturing establishments (Martin *et al.* 1991).

Rice *et al.* (2006) find that the portion of the variation in average regional wages in Britain attributable to productivity differences is positively related to the volume of population accessible within specified ranges of travel time. Summarizing across these studies, larger or more dense population is generally associated with greater productivity, but the extent differs widely by industry, region or country examined, time frame, and estimation technique.

Critics of the simple size proxy for agglomeration have noted that it may confound urbanization with localization economies and may also capture urban diseconomies along with agglomeration benefits (Carlino 1979; Moomaw 1981a; 1983a; 1983b; Begovic 1992; Ciccone and Hall 1996). Several studies have examined nonlinearities in the relationship between urbanization and productivity, finding increasing disbenefits of urbanization at the large end of the scale that suggest accumulating congestion, pollution, or other disamenities (Kawashima 1975; Fogarty and Garofalo 1978; 1988). Sveikauskas *et al.* (1985) demonstrate a strong agglomeration benefit for manufacturing plants in Brazil's São Paulo state using the unusual urbanization measure of travel time to the city of São Paulo, and Graham (2007) and Graham and Kim (forthcoming) find that the productivity of small British firms is enhanced by agglomeration as indicated by accessibility to other employers.

2.4.2.2. Urbanization versus Localization

Another approach incorporates multiple indicators to distinguish urbanization from localization economies. While both types of agglomeration economies are most often indicated by level measures (i.e., population size, own-industry employment or value-added), density measures are also common (i.e., population or employment density, location quotients). Shefer (1973) estimates U.S. manufacturing industries to have higher productivity both in the presence of larger metropolitan own-industry employment (localization economies) and greater regional total manufacturing employment (urbanization economies). Carlino (1979) associates localization economies with the ratio of local to national industry employment and includes both population and establishment counts to measure urbanization economies and diseconomies. His results indicate that urbanization economies and diseconomies are generally more significant than localization economies in U.S. metropolitan areas, but the comparisons vary widely across two-digit SIC (Standard Industrial Classification) manufacturing sectors. Modifying his earlier (1985) study by adding industry employment and population as separate indicators of localization and urbanization economies, respectively, Moomaw (1986) finds that for most industries the declining urban productivity differential is more closely associated with localization than urbanization economies, but also that several industries present the opposite pattern. Examining manufacturing in both the United States and Brazil, Henderson (1986) finds localization but not urbanization economies to be significant determinants of productivity. Four studies by Moomaw (1988; 1998), Lee and Zang (1998), and Pan and Zhang (2002) affirm Henderson's conclusion that localization economies are the more important type of agglomeration economy for the majority of manufacturing industries, but also reveal substantial urbanization economies or diseconomies in several sectors. In contrast, Sveikauskas *et al.* (1988) show that once raw materials locations are taken into account, the U.S. food products industry evidences only urbanization externalities. They reason that other empirical research may mistake the benefits of natural resource proximity for localization economies. Nakamura (1985) estimates productivity separately for different manufacturing industries in Japan. Incorporating the assumption of constant returns to scale at the firm level, any non-constant returns to scale at the industry level are taken to represent localization economies. Nakamura discovers urbanization economies (population size) to be more important for light manufacturing industries and localization economies for heavy manufacturing industries. Using plant-level data, Feser (2001b) finds substantial urbanization economies in the high-technology measuring devices industry and localization economies in the lower-technology farm and garden machinery equipment industry. Lall *et al*. (2004) adopt density indicators to study manufacturing industries in India, finding that localization economies return larger benefits for higher-technology industries and that diseconomies either offset or outweigh the advantages of urbanization. In a small-sample study of high-technology firms in Milan, Capello (2002b) produces evidence suggesting that urbanization economies are more important for large firms and localization economies for smaller firms. Mukkala (2004) reports greater beneficial effects of localization compared to urbanization economies in three Finnish manufacturing sectors, measuring both concepts with density measures, and Tveteras and Battese (2006) demonstrate the existence of both localization economies and diseconomies from own-industry size in Norwegian salmon aquaculture.

Although productivity is the most common dependent variable in empirical agglomeration economy studies, alternative measures of economic performance might be considered to be variations on a theme. Rosenthal and Strange (2004) discuss the merits of four possible substitutes for analyzing urban agglomeration benefits: regional growth, firm births, wages, and rents. The last two are useful primarily for analyses of city size, since wages and rents data generally are not available by industry (Eberts and McMillen 1999). One study of New England counties finds urbanization economies to be more influential than localization economies in raising average earnings except in the financial services, insurance, and real estate sector, with little evidence of agglomeration benefits spilling over across counties (Hanink 2006). Employment growth is the focus of a number studies described later (section 2.4.2.3) (namely, Glaeser *et al.* 1992; Henderson *et al.* 1995; Henderson 1997; Combes 2000; Acs *et al.* 2002b; Chen 2002; Hoogstra and van Dijk 2004). In addition, several studies of U.S. metropolitan or county employment growth conclude that localization is more important to both manufacturing and services industries than urbanization economies, though the correspondence between the agglomeration concepts and the measures used to operationalize them typically is tenuous (O hUallachain 1989; O hUallachain and Satterthwaite 1992; Desmet and Fafchamps 2005).

New firm formation is positively associated with a variety of urbanization and localization agglomeration factors, including population density, population growth, entrepreneurial resources, smaller average plant size, local industry size or concentration, transportation infrastructure, more government spending, a larger white-collar workforce, and the availability of knowledge capital and spillovers (Audretsch and Fritsch 1994; Keeble and Walker 1994; Reynolds *et al.* 1994; Harhoff 1999; Armington and Acs 2002; Figueiredo *et al.* 2002; Gabe 2003; Hackler 2003; Acs and Armington 2004b; Holl 2004a; 2004b; 2004c; Lee *et al.* 2004; Audretsch and Keilbach 2007; Fritsch and Falck 2007). Swedish firm birth rates are more closely associated with localization than urbanization economies, and firm deaths are less strongly tied to both sources of agglomeration economies (Nystrom 2007). Renski (2006) reveals that new firm survival rates in the United States are enhanced by localization economies, though the effects are modest and vary substantially across industries and different sources of agglomeration externalities. According to Acs *et al*. (2007), the survival of new firms in the United States services sector is positively associated with urbanization economies but negatively associated with localization economies. New firm formation has greater long-term impacts on employment growth in more densely populated regions (Acs and Mueller 2008; Fritsch and Mueller 2008; van Stel and Suddle 2008).[13] Guimaraes *et al*. (2000) find that the locations in Portugal of new establishments owned by foreign firms are related to both urbanization and localization economies, and are influenced in particular by concentration of activity in the business services sector; similar results have been obtained for the United States (Luger and Shetty 1985; Kim *et al.* 2003). Foreign-owned plants in France are lured in terms of location choice by proximity to other plants in the same industry (Crozet *et al.* 2004). Although there are differences across industries and countries of ownership in terms of the magnitude of the effect, the marginal attraction from an existing foreign plant is substantially greater than for a domestic plant, but the overall patterns of foreign site investments largely follow the spatial distribution of French industry establishments due to their numerical dominance. Exceptions to the trend do exist. For instance, Reynolds (1994) reports population density to be related to lower firm births in the manufacturing sector in the United States, and Arauzo-Carod and Teruel-Carrizosa (2005) discover that firm birth rates are greater in smaller-sized Spanish

[13] Mueller *et al.* (2008) find regional differences in employment impacts in Great Britain according to levels of entrepreneurial activity but not population density.

municipalities. Rosenthal and Strange (2003) also concentrate on firm births and new-firm employment (this study is discussed in detail in section 2.5).

There are additional possibilities as well. Localization and urbanization economies, measured as the areal density of supplier and purchaser production, lower average costs in the U.S. food manufacturing industry (Cohen and Morrison Paul 2005). Proximity to agricultural production (suppliers) is beneficial within states and across neighboring states. The profitability of Indian manufacturing firms is boosted by localization economies (Kambhampati and McCann 2007). Harrison *et al.* (1996) find urbanization but not localization influential in predicting the adoption of programmable automation technology in U.S. metalworking plants. For precision machining operations, urbanization and localization economies do more to speed the adoption of computer numerical control technology for smaller establishments (Kelley and Helper 1999). The intensity of formal interfirm information transactions in the semiconductor industry is insensitive to spatial proximity except at the continental scale (Arita and McCann 2000). Urbanization does not seem to boost either the incidence or the intensity of private research and development activity in Denmark (Smith *et al.* 2002). In northern Israel, urbanization is positively related to innovation for electronics manufacturers and high-technology manufacturers in general but not for plastics or metals firms; urbanization does not affect the innovation propensity of technology-intensive plants in Ireland (Shefer and Frenkel 1998; Frenkel *et al.* 2003). Acs and Varga (2005) report that urbanization economies facilitate innovation in the form of patent applications in European nations. Evaluating data from several business surveys, Gordon and McCann (2005) conclude that patterns of innovation across metropolitan London can best be explained by urbanization externalities rather than the localization of economically-related activity or networks of interactions. Localization improves the innovation performance of Spanish biotechnology firms (Quintana-Garcia and Benavides-Velasco 2006). Although results vary substantially by sector, the intensity of research and development in Belgian firms is more frequently positively associated with the R&D intensity of firms in the same industry (localization) than firms in all other industries (urbanization) (Bertinelli and Nicolini 2005). The propensity of manufacturers to export typically is influenced by both localization and urbanization economies; the extent to which this relationship exists depends on the particular industry, nation, and firm size (Costa-Campi and Viladecans-Marsal 1999; Malmberg *et al.* 2000; Chevassus-Lozza and Galliano 2003; Belso-Martinez 2006; Becchetti *et al.* 2007; Silvente and Gimenez 2007). In the southern United States, however, the gap between the proportion of urban and rural manufacturers that export is better explained by information spillovers and networking opportunities than localization economies (Eff and Livingston 2007). Co-located plants within high-technology industries tend to have greater employment growth than isolated establishments, a phenomenon that may be due to knowledge spillovers or other localization economies (Audretsch and Dohse 2007). Residents of densely populated and fast-growing regions are more likely to become entrepreneurs (Wagner and Sternberg 2004; 2005). Strange *et al.* (2006) postulate that urbanization and localization may be responses to different types of uncertainties faced by firms, and test this hypothesis using an innovation survey of Canadian manufacturers. Indeed, they find that plants located in larger areas report higher levels of uncertainty concerning technology and innovation, whereas plants that describe substantial uncertainties in terms of future labor skill needs tend to be located in metropolitan areas with greater employment in their own industry.

A number of recent studies examine geographic concentration as an outcome of agglomeration economies. Ellison and Glaeser (1999), Kim (1999), and Dumais *et al*. (2002) observe that the levels of geographic concentration in manufacturing can only partially be explained by natural resource endowments, providing indirect evidence of agglomeration economies. Long-run trends in the United States as well as in Ireland and Portugal do not show high-technology industries to be more geographically concentrated than less technology-intensive sectors, a spatial pattern that might be expected if external economies such as knowledge spillovers were the major impetus behind localization (Kim 1995; Barrios *et al.* 2005), but cross-sectional analyses of French, German, and Portuguese manufacturing do reveal the expected outcome to some degree (Maurel and Sedillot 1999; Alecke *et al.* 2006; Guimaraes *et al.* 2007). Several studies demonstrate that plants sited in locations where their industry is concentrated tend to be larger on average, particularly in manufacturing industries (Holmes and Stevens 2002; Barrios *et al.* 2006a; Wheeler 2006; Lafourcade and Mion 2007). This could be evidence of localization benefits, though the result may also derive from different locational preferences or survival rates of newer, smaller firms. In a series of papers, Feser and Sweeney use a case-control study design to analyze spatial clustering in manufacturing industries relative to a control group of randomly selected establishments. The spatial concentration of the controls accounts for the baseline tendency of businesses to follow the general clustering patterns of human settlements. Medium-sized and independent establishments are the most likely to co-locate (Sweeney and Feser 1998). Localization advantages are a likely explanation: very small plants may have too little production volume to benefit from agglomeration, whereas the largest plants and those belonging to multi-locational firms may rely more heavily on internal economies. Furthermore, members of more knowledge-intensive industries, those that presumably have the most to benefit from knowledge spillovers, are also more likely to co-locate (Feser and Sweeney 2000; 2002). Co-location tendencies are evident in the spatial patterns of firm births in New York's advertising industry (Arzaghi and Henderson 2006) and Canadian biotechnology (Aharonson *et al.* 2007). Roos (2005) conducts an ANOVA decomposition analysis, concluding that the influence of agglomeration economies, or spatial clustering following established patterns of human activity, are far more important in inducing spatial concentration of production in Germany than are features of the physical and political geography. Kim *et al.* (2000) report that within rural areas, industries are more likely to be spatially concentrated (as measured at the county level) if they have larger average plant size, higher fractions of non-subsidiary plants, greater labor intensity in production, and less reliance on local input markets. Service, finance, insurance, and real estate establishments in Houston, but not manufacturing and energy companies, are more likely to be located in employment centers offering greater localization and urbanization economies (Kohlhase and Ju 2007). Examining eight manufacturing industries in three Indian metropolises, Chakravorty *et al*. (2005) find little evidence of localization economies from buyer-supplier networks or labor pools at the intraurban scale. Establishments and employment tend to cluster in mixed use industrial districts; location choices are limited and are driven mostly by state regulation, available land, and generalized urbanization economies. Viladecans-Marsal (2004) directly relates agglomeration measures with the tendency of Spanish manufacturers to concentrate spatially. Her results are reminiscent of Nakamura's for Japan twenty years prior: the concentration of high-technology firms is closely related to several measures of urbanization economies, including population and employment per capita, whereas other companies are more responsive to own-sector employment, i.e., localization economies. She also finds spatial spillovers from neighboring cities to be significant for some industries.

The mass of empirical research considering urbanization and localization economies presents a bewildering variety of results. Some analyses support the importance of both types of externalities, some signify greater importance for one type or the other, and many have yielded results that differ dramatically across industry sectors. Certainly the variety of geographic locations, scales, and methodologies make it tricky to reach consistent conclusions across the literature. The concepts themselves may also be to blame, however. Urbanization and localization may not be adequate classifications relative to Marshall's agglomeration economy concepts of specialized inputs, labor pooling, and knowledge spillovers. First, the urbanization and localization categories are adopted for empirical convenience, rather than on the basis of strong theory. It is not proximity to other businesses, per se, that advantages firms, but rather the interactions, spillovers, and cost reductions that are enabled by the spatial grouping of businesses. The appropriate application of the concepts of urbanization and localization may vary across industries and even firms (Feser 1997; 2001a; 2001b). At the very least, separating urbanization and localization economies does not help to distinguish among Marshall's sources of agglomeration economies since the three types all fall into the localization category. Second, there is the task of determining what constitutes an industry with respect to which localization economies may be measured. Typical industry classifications, including the U.S. Standard Industrial Classification system and its successor, the North American Industry Classification System, are based principally on primary product similarity, which need not be congruent with production technology or labor needs and does not account for secondary products. Moreover, it is not apparent how much aggregation is appropriate. Industry sectors defined at too aggregate a level combine plants that experience agglomeration externalities in different fashions and to different degrees, whereas classifications that are too disaggregate exclude firms that are similar enough to interact with each other to produce localization benefits (Moomaw 1998; Renski 2006). As a practical matter, disaggregate industry definitions also diminish working sample sizes.

2.4.2.3. Marshall-Arrow-Romer, Jacobs, and Porter Externalities

Instead of focusing on the division between localization and urbanization economies, numerous empirical studies test three postulated types of knowledge spillover externalities: Marshall-Arrow-Romer (industrial specialization or localization), Jacobs (industrial diversity), and Porter (competitive rivalry). These concepts often are presented not as specifically linked to knowledge spillovers, but as gross measures of regional industrial structure. Industrial diversity is measured as the inverse of concentration, most commonly using either a Hirschman-Herfindahl index or a Gini coefficient, or by the fraction of employment in the largest few industries (excluding the study industry). Location quotients indicate industrial specialization, and competition is proxied by the ratio of establishments to workers, often also normalized with respect to a larger reference region. The dominant outcome measure is employment change, but various other outcomes of interest, such as productivity and patenting, have been examined as well.

Glaeser *et al.* (1992) analyze employment growth in the largest industries in urban conglomerations of counties in the United States from 1956 to 1987, finding support for local competition (Porter) and diversity (Jacobs) externalities improving performance, but not for own-industry (Marshall-Arrow-Romer) externalities. Henderson *et al.* (1995) examine eight U.S. manufacturing industries, finding Marshall-Arrow-Romer externalities to be key to employment growth in traditional, mature sectors, and both Marshall-Arrow-Romer and Jacobs externalities important for high-technology industries. They suggest that industrial diversity is important for attracting new industries but that industrial concentration is key for retention. In a complementary study, Henderson (1997) uses panel data for five manufacturing industries to demonstrate that knowledge spillover externalities entail significant time lags, with both Marshall-Arrow-Romer and Jacobs types tending to reach maximum effect only after four or more years and Jacobs benefits persisting at substantial levels beyond seven years. Beardsell and Henderson (1999) find significant benefits from Marshall-Arrow-Romer externalities but not Jacobs externalities for non-subsidiary plants in the U.S. computer industry; for subsidiary plants neither type of externality is important. Using plant-level panel data with fixed establishment effects, Black and Henderson (1999) present evidence only of Marshall-Arrow-Romer externalities for high-technology plants, with no agglomeration externalities at all in capital-goods industries. Industrial diversity is one of the variables that determines differences in manufacturing labor productivity across metropolitan regions (Essletzbichler and Rigby 2002). Both Acs *et al.* (2002b) and Henderson (2003), however, fail to uncover evidence of Jacobs-type spillovers for high-technology industries in the United States. Henderson does report significant Marshall-Arrow-Romer externalities with regard to high-technology productivity (but not for lower-technology machinery plants), and also finds that independent establishments obtain more benefits from agglomeration economies than branch plants. Lim (2007) finds evidence of Marshall-Arrow-Romer externalities from metropolitan specialization in technology-intensive industries, but no benefits arising from diversity or competition in the high-technology sector.

Results from other nations are just as varied. Harhoff reports firm formation in German high-technology industries to benefit from industrial diversity and specialization (1999). Examining 94 French manufacturing and service industries at the regional level, Combes (2000) discovers that, not surprisingly, industrial diversity typically has a positive influence on service employment but negatively impacts manufacturing. Except within a few isolated industries, local sectoral specialization detracts from employment growth. Canadian employment growth is positively associated with industrial diversity (Shearmur and Polese 2007). New firm formation and employment growth in the Netherlands benefit from industrial specialization, competition, and diversity, as well as urbanization (Hoogstra and van Dijk 2004; van Oort and Atzema 2004; van Soest *et al.* 2006; van Oort 2007). These results differ by broad industry sector, though, and the positive effects of agglomeration economies diminish rapidly with distance. Distinguishing between two types of industrial diversity, Frenken *et al*. (2007)

demonstrate that diversity within Dutch industrial sectors aids employment growth but slows productivity growth, whereas diversity considered across the entire economy is more important for insulating employment against shocks. In the same nation, the growth of value-added appears to be aided most by a competitive environment for manufacturing and construction firms, and by industrial diversity for the services and trade sectors (Van Stel and Nieuwenhuijsen 2004). In South Korea, Henderson *et al.* (2001a) finds that own-industry concentration benefits labor productivity in all manufacturing industries but local industrial diversity only affects plants in technology-intensive industries. Urbanization (measured by the logarithm of population) is universally unimportant. Lee *et al.* (2005) report nearly opposite conclusions: competition aids productivity growth, industrial diversity is beneficial for all manufacturing industries *except* the most technology-intensive, and own-industry concentration has no significant influence. Investigating Spanish manufacturers, de Lucio *et al.* (2002) produce no significant evidence of externalities arising from either competition or industrial diversity; industrial specialization impacts value-added growth positively at relatively high levels but negatively at lower levels of specialization. Specialization but not diversity aids productivity growth in Spanish regions (Serrano and Cabrer 2004). In Portugal, industrial diversity and total population but not local specialization is associated with firm births, whereas manufacturing plant relocations are drawn by sizeable local industry activity (Holl 2004a; 2004c). Almeida (2007) finds industrial concentration to be beneficial and more important in most sectors than competition or diversity. Similar studies in Spain obtain contradictory results concerning the relative importance of industrial diversity and specialization vis-à-vis new establishment formation (Holl 2004b; Arauzo-Carod 2005). Moroccan urban areas benefit in terms of production from specialization and industrial diversity but not competition (Bun and El Makhloufi 2007). Local competition has small positive effects and industrial diversity large positive effects on employment and wage growth in Taiwanese cities (Chen 2002). In Japanese regions, total factor productivity growth is boosted by the spatial density of own-industry output or employment in the finance, services, and trades sectors, but manufacturing productivity is unaffected (Dekle 2002). Local competition is important in the services and trade sectors only; diversity externalities are unimportant. Industrial diversity but not specialization reduces production costs for Indian manufacturers (Lall and Chakravorty 2005). Foreign firms siting manufacturing establishments in Ireland are more likely to select industrially diverse counties, and firms in less technology-intensive industries are also drawn to locations where the industry is relatively concentrated (Barrios *et al.* 2006b; Barrios *et al.* 2006c). The resulting coagglomeration of Irish with foreign-owned plants augments productivity and employment in the domestic establishments.

With regard to innovation outcomes, Feldman and Audretsch (1999) make use of a Small Business Association (SBA) tally of documented product and process advances in the U.S. to reveal that local competition and industrial diversity (restricted to complementary industries) promote innovations but that specialization does not; a plant survey in the United Kingdom also reveals insignificant influence from industrial specialization (Roper *et al.* 2000). Lim's (2004) analysis of patents in high-technology industries across U.S. metropolitan areas shows that benefits arise from both specialization and diversity but not local competition. Externalities associated with industrial diversity appear to spill across neighboring regions, whereas those from specialization do not. Similarly, Ketelhohn (2006) reports that specialization and diversity, as well as proximity to potential purchasers, increase the numbers of cited semiconductor patents in United States counties, but that competition does not. On the other hand, Carlino *et al*. (2007) find that metropolitan per capita patenting rates are positively associated with competition and employment density but not industrial diversity. Patent applications across Europe are positively associated with industrial specialization, and though the results for diversity are mixed overall, technology-intensive sectors gain more benefits from industrial diversity (Paci and Usai 1999; 2000; Greunz 2003b; 2004; Parent and Riou 2005; Moreno *et al.* 2006; Maggioni *et al.* 2007). In Sweden patents are stimulated by all three types of externalities (Andersson *et al.* 2005; Ejermo 2005). European branches of foreign-owned multinational corporations patent at higher rates in regions featuring industrial diversity, local specialization in the same industry (considering only other foreign-owned firms), and urbanization economies (Cantwell and Piscitello 2005). Dutch labor costs for research employees, a proxy for innovation intensity, are higher in municipalities with greater industrial diversity and competition (van Oort 2002). Software development firms in the Netherlands take advantage of localization economies that enable innovations to be produced with relatively smaller amounts of labor input, whereas regional industrial diversity and urbanization do not seem to be helpful (Boschma and Weterings 2005). Koo (2005b; 2007) employs a simultaneous equations approach to account for endogeneity among agglomeration, technology spillovers, and the rate of technological change, revealing substantial beneficial influences from same-industry and competitive externalities in the multiple-equation system.

Taken together, the plethora of studies comparing the three types of knowledge spillovers yields a web of results as intricate as that regarding urbanization and localization economies. Although the preponderance of empirical research shows that own-industry specialization, industrial diversity, and local competition can yield important benefits, their influences vary substantially depending on the industry, outcome measure, and geographic region or spatial scale examined (van Oort 2007). Nor does this branch of research escape the major deficiencies of the urbanization versus localization dichotomy: there is no definitive way to demarcate industry boundaries so as to distinguish Marshall (own-industry) from Jacobs (industrial diversity) externalities, the concepts themselves may diverge across industries or firms, and the approach does little to establish a clearer understanding of the relative influences of the three original Marshallian agglomeration economies.

2.4.2.4. Knowledge Spillovers

There has been growing attention paid to dynamic externalities, spillovers that create benefits that are realized over the long run (Glaeser *et al.* 1992; Feser 1998a; Feldman 1999; Breschi and Lissoni 2001; Autant-Bernard *et al.* 2007; Henderson 2007). Although these analyses may not be billed as studies of agglomeration economies, they aim to explain dynamic outcomes of interest, including innovation, learning, and technical progress, on the basis of knowledge spillovers. Perhaps the strongest evidence of knowledge externalities arises using patent information, as one of the few easily measurable outcomes associated with innovation (though certainly not one without flaws; see Acs *et al.* 2002a; Sampat *et al.* 2003; Hipp and Grupp 2005). Patent citations reveal substantial localization, i.e., a high degree of citing patents originating in the same city, state, or region as the cited patent, strong evidence that knowledge diffusion is mediated by spatial distance (Jaffe *et al.* 1993; Adams and Jaffe 1996; Almeida 1996; Jaffe and Trajtenberg 1996; Almeida and Kogut 1997; Co 2002; Maurseth and Verspagen 2002; Verspagen and Schoenmakers 2004; Koo 2005c; Agrawal *et al.* 2006; Co 2006; Fischer *et al.* 2006; Koo 2006; LeSage *et al.* 2007; Sonn and Storper forthcoming). Co-authored patents are also more likely between regions that are geographically proximate (Maggioni *et al.* 2007). (The importance of distance may be declining over time: see O hUallachain and Leslie 2005; Johnson *et al.* 2006). Patterns of patents demonstrate both time and spatial lags (Fischer and Varga 2003; Sampat *et al.* 2003; Bode 2004; Parent and Riou 2005); institutional and political (national) boundaries hamper but do not halt the diffusion of patent knowledge (Jaffe and Trajtenberg 1996; Tijssen 2001; Maurseth and Verspagen 2002; Bottazzi and Peri 2003; Cantwell and Iammarino 2003; Greunz 2003a; Moreno *et al.* 2005a; Fischer *et al.* 2006; LeSage *et al.* 2007). Patent concentrations do not match industry employment configurations, however, suggesting that knowledge and production need not occur in the same location (Kelly and Hageman 1999; Ceh 2001; Koo 2005a; Moreno *et al.* 2006; for a contrary result, see Moreno *et al.* 2005b). In a study investigating the determinants of technological and macroeconomic change in Hungarian counties, Varga and Schalk (2004) find local knowledge spillovers, proxied by patents, to be important even after accounting for knowledge spillovers at the domestic and international levels. As a dependent variable signifying innovation, there is evidence that patenting rates are higher in locations possessing greater urbanization economies, higher levels of human capital and industrial research and development, and more university activity (O hUallachain 1999; Autant-Bernard 2001; Bottazzi and Peri 2003; Greunz 2003a; Porter 2003; Riddel and Schwer 2003; Sedgley and Elmslie 2004; Andersson and Ejermo 2005; Greunz 2005; Moreno *et al.* 2005a; Knudsen *et al.* 2007; see Gossling and Rutten 2007 for a contrary finding). Several studies have used patenting rates to compare the effects of Marshall-Arrow-Romer, Jacobs, and Porter externalities (section 2.4.2.3 above).

Alternatives to patents as a source of innovation data are relatively scarce. The one-time (1982) United States Small Business Association innovation database has been mined thoroughly. Researchers examining the database contend that, for appropriate industries, innovation counts are at least as a good a measure of innovation as patents; analyses substituting innovation counts for patents reach similar conclusions but more strongly (Acs and Audretsch 1989; Acs *et al.* 1992; Feldman and Florida 1994; Audretsch and Feldman 1996; Acs *et al.* 2002a). Unfortunately, the database has never been updated or replicated. Using the 1999 Canadian Survey of Innovation, Therrien (2005) demonstrates that firms located in larger cities have greater production rates of world-leading innovations, but when the definition of innovation encompasses both technology creation and adoption, firm innovation does not vary systematically with city size. Oerlemans and Meeus (2005) use a survey to relate the innovation performance of Dutch firms to networking activity, local purchasing and sales relationships, and localized spillovers. For Finnish technology firms, product innovations are negatively associated with population density but process innovations and the number of new products introduced to market are unrelated to population density (McCann and Simonen 2005). Wallsten (2001) reveals indications of highly localized knowledge spillovers in the spatial patterns of grants awarded by the Small Business Innovation Research (SBIR) program. The number of neighboring recipient firms is a strong predictor of an observed firm's program participation status, but only up to a distance of approximately five miles. Rosenbloom (2007) reports substantial geographic concentration at the intermetropolitan level in both SBIR and Small Business Technology Transfer (STTR) grants.

Research and development activity has been documented to be an important source of knowledge spillovers. For example, Sena (2004) finds indirect evidence of knowledge spillovers in that the productivity growth of Italian chemical manufacturing firms with relatively low investment and R&D expenditures is positively related to estimates of technical change in the nearest high-R&D and high-investment chemical firms. The benefits of R&D activity are localized, diminishing with geographic as well as technological distance.[14] This holds for industry, university, and public laboratory R&D (Adams and Jaffe 1996; Varga 1997; Jaffe *et al.* 1998; Anselin *et al.* 2000; Autant-Bernard 2001; Bode 2004; Fritsch and Franke 2004; Funke and Niebuhr 2005; Autant-Bernard 2006; Aharonson *et al.* 2007; Johansson and Karlsson 2007; Lehto 2007), though there is evidence that the externalities arising from university-based R&D are more spatially constrained than from industrial research (Adams 2002; Beugelsdijk and Cornet 2002; Greunz 2003a; 2005).[15]

[14] Technological distance refers to the degree of dissimilarity between the product or field focus of the R&D conducted and of the spillover recipient; smaller distances imply greater concordance.

[15] Autant-Bernard (2006) notes that studies of France consistently obtain the opposite result: while private research yields knowledge spillovers that decline with increasing distance, knowledge spillovers from public research seem not to be substantially bounded by geographic proximity.

Much of the analytical focus has been on the R&D performed by universities and federal laboratories, since data are not readily available for private-sector industrial research. University R&D is associated with patenting, innovative activity, and new firm formation within U.S. states and metropolitan areas, and also spurs industrial R&D that leads to additional innovation and spillovers (Jaffe 1989; Anselin *et al.* 1997; Kirchhoff *et al.* 2002a; Woodward *et al.* 2004; Kirchhoff *et al.* 2007). University research publications and related industrial patents are highly co-located, at least for the specific fields of medical imaging, neural networks, and signal processing (Agrawal and Cockburn 2003). Spin-off firms have a very strong likelihood of locating in close proximity to the establishing university; the same holds for non-spin-off entrant firms that have strong ties to university research (Zucker *et al.* 1998; Candell and Jaffe 1999). Small firms benefit more from university R&D spillovers than large companies (Acs *et al.* 1994); in contrast, larger as well as newly formed firms benefit more from public laboratory research (Cohen *et al.* 2002). Knowledge externalities from universities have a substantial spatial range that can extend well beyond U.S. metropolitan area boundaries (Anselin *et al.* 2000; Woodward *et al.* 2004; Goldstein and Drucker 2006).

Knowledge spillovers can arise from other university activities including industry-university collaborations, local networking, personnel migration, and the creation of human capital, but these sources are much more difficult to document (Goldstein *et al.* 1995; Goldstein and Renault 2004; Moretti 2004; Drucker and Goldstein 2007). University knowledge production does tend to raise average regional wages; there is mixed evidence, however, as to whether regions must attain a certain overall size or assemble a critical mass of private-sector activity in related fields in order to benefit from local university spillovers (Varga 2000; 2001; Goldstein and Renault 2004; Koo 2005c; Goldstein and Drucker 2006).

2.4.2.5. Marshall's Agglomeration Economies

Several recent studies have followed a different strategy, employing more refined constructs to measure several sources of agglomeration externalities explicitly and concurrently. These indicators tend to be relatively complex, often combining multiple data sources in the effort to adequately measure access to specific agglomeration economies at the local level. For instance, Dumais *et al*. (1997) examine the relationship between employment growth and Marshall's three agglomeration economies. Supply chain externalities are indicated by proximity to plants in supplying and purchasing industries, whereas their labor pooling variable incorporates a measure of the similarity of occupational mix at the state level to that employed by the industry. Information spillovers are represented both by a technology flow variable and a measure of the degree of co-ownership of plants across different industries by the same firm. They find modest benefits from proximity to input suppliers and output purchasers and stronger effects from labor pooling and intellectual spillovers.

Feser (2001a; 2002) calculates six distance-weighted measures of access to Marshallian agglomeration economies at the establishment level: labor pooling, input suppliers, producer services, intermediate purchasers, and two indicators of knowledge spillovers, patenting rates and university research and development (R&D) expenditures. Only the input suppliers variable is significant overall for the farm and garden machinery industry, but for the largest establishments producer services are also important.

Producer services, labor pooling, and university R&D all enhance productivity for manufacturers of measuring devices and instruments, and university proximity benefits small independent plants the most. Feser (2002) also investigates one aspect of regional industrial organization by including a control measuring overall concentration in the manufacturing sector, finding a strong negative association between manufacturing dominance and productivity in the measuring and controlling devices industry, but a statistically insignificant relationship for farm and garden equipment establishments. The paper is a crucial precursor of this study: although Feser does not model industry-specific dominance or test the intervening effect that dominance might have on firms' realization of agglomeration economies, he sets the stage for this analysis by incorporating regional industrial structure as a factor determining plant-level performance in a production function context.

Rigby and Essletzbichler (2002) construct plant-level indicators of supply chain concentration, labor pooling, and embodied technological spillovers, and include metropolitan size among the control variables in a set of regressions with labor productivity as the dependent variable. They obtain relatively weak results, especially at the four-digit SIC level of industry aggregation (for which they blame plant-level heterogeneity and outliers), but do establish that each of the three Marshallian agglomeration variables is significant and positive in at least a subset of the manufacturing sectors tested. Metropolitan size, proxying urbanization economies, is beneficial in several of the sectors that have relatively low levels of technology. Acs and Armington (2004a) track entrepreneurial activity as an observable indicator of knowledge spillovers, using new firm births and business proprietors as a share of the workforce as their independent variables. New firm births are strongly associated with regional employment growth in non-manufacturing sectors, but the proprietor measure is insignificant. Renski (2006) relates plant survival to a variety of specific Marshallian agglomeration economies, revealing localization measures to have positive but relatively modest benefits that differ sharply across industries. He includes a measure of regional dominance by large plants that is not industry-specific, but it demonstrates little impact. For the special case of the Netherlands, van der Panne and Dolfsma (2003) report that proximity to universities and private research institutes is associated with greater numbers of establishments and employment in high-technology firms, but indicators of worker education levels in the local labor market, population density, and distance between town centers are unimportant. Koo (2005b; 2007) estimates input pooling, labor pooling, and knowledge spillovers, finding input pooling to produce the most significant advantages. In addition, Andersson *et al*. (2007), Power and Lundmark (2004), and Freedman (2006) use data linking workers with firm characteristics to provide unusually direct evidence of Marshall's labor pooling externality.

In a somewhat different approach, Rosenthal and Strange (2001) concentrate on the probable importance of agglomeration economies rather than potential access to them. They relate indicators of the value of knowledge spillovers, labor pooling, and input sharing to spatial agglomeration of industries at the state, county, and zip code geographic levels, while controlling for natural resource location and product transport costs. Labor pooling, measured by net labor productivity, the share of management-type workers, and the percentage of workers with college degrees, has the largest impacts on concentration at all three geographic levels. Higher rates of knowledge spillovers (adapted from the SBA innovations database) are positively associated with agglomeration only at the smallest (zip code) geography, whereas input availability (manufactured and non-manufactured inputs per dollar of shipment) is important at the largest (state) level. Kerr *et al*. (2007) refine this tactic, relating pairwise coagglomeration of manufacturing industries to proxies of possible interindustry connections occurring through input-output relationships, labor pooling, and knowledge spillovers. They find that all three sources of agglomeration economies are related to co-location among pairs of industries, with purchasing and supplying relationships yielding the strongest positive association.

Renski and Feser (2004) explicitly compare proxies for localization and urbanization economies with more direct measures of Marshallian agglomeration externalities. They create indicators of labor pooling, specialized input supply networks, intermediate goods markets access, and knowledge spillovers and test them against population size (urbanization) and own-industry employment (localization). Interestingly, the four direct agglomeration measures tend to be more highly correlated with urbanization than localization economies, demonstrating that Marshall's advantages may pertain in practice to spatial conglomerations of businesses that are treated as dissimilar by standard industrial classification schema.

Regardless of the theoretical and conceptual advantages, the approach of specifying explicit agglomeration indicators entails practical shortcomings, chief among them the problems of obtaining suitable data and of encountering substantial multicolinearity that makes it difficult to distinguish among multiple agglomeration economy measures (Renski and Feser 2004). It is not coincidental that nearly all of the studies adopting this research strategy use micro-level data. Not only does information on individual establishments support a finer grained analysis, illuminating the influences of plant-specific characteristics, it also allows for larger sample sizes and increases the variation represented in the constructed measures. Even so, conceptual parallels and statistical overlap (i.e., multicolinearity) among the agglomeration variables remain a thorny issue (see section 5.7).

The chief expansion in research using micro-level data comes from increasing use of government-collected datasets.[16] These data are nearly always confidential, but may be used to develop aggregated statistics or analyses. Gabe (2003) uses *Covered Employment and Wages* (also known as ES-202) data from the state of Maine; Acs *et al*. (2002b) and Renski (2006) analyze the same data from the U.S. Bureau of Labor Statistics on a nationwide basis. The U.S. Census Bureau's *Longitudinal Employer Household Database* (LEHD) matches workers with firms (but not establishments) (Freedman 2006; Andersson *et al.* 2007); the *Longitudinal Establishment and Enterprise Microdata* (LEEM) tracks establishments over time (Armington and Acs 2002; Acs and Armington 2004a; 2004b; Lee *et al.* 2004; Acs *et al.* 2007; Acs and Mueller 2008); and the *Standard Statistical Establishment List* provides physical locations (Arzaghi and Henderson 2006). The *Longitudinal Research Database* (LRD) is also constructed and maintained by the U.S. Census Bureau, and though it is restricted to manufacturing

[16] There are several other potential sources for plant-level data. Business surveys collecting primary data have been used rarely in productivity research due to their expense and potential unreliability (examples include Sveikauskas *et al.* 1985; Ke 1995; Lublinski 2003) but are more common with regard to studies of outcomes such as technology adoption or export activity. Tax returns or other official documents can reveal useful information but are generally limited in scope, coverage, and accessibility (e.g., Capello 2002b). Within the past fifteen years or so, the Dun & Bradstreet company has improved the coverage and accuracy of its *MarketPlace* (United States) database to the point where the information, publicly available for purchase, can (with caveats) support rigorous research (e.g., Reynolds 1994; Rosenthal and Strange 2001; 2003; Kohlhase and Ju 2007). Nevertheless, *MarketPlace* is collected primarily as a marketing resource and does not include detailed input data.

plants, it covers almost all such establishments in the United States (see section 5.2). The primary advantages of the LRD from a research standpoint are that it contains large and statistically representative samples, provides detailed information on outputs and inputs including capital, and is easily linked with other datasets (Bartelsman and Doms 2000). This database has been used by quite a few of the analyses detailed earlier (Martin *et al.* 1991; Adams and Jaffe 1996; Dumais *et al.* 1997; Black and Henderson 1999; Feser 2001a; 2001b; Essletzbichler and Rigby 2002; Feser 2002; Rigby and Essletzbichler 2002; Henderson 2003; Kerr *et al.* 2007) and supplies the data for this dissertation as well. Establishment- or firm-level datasets are available for many other nations, often with fewer confidentiality restrictions than in the United States.[17]

2.4.2.6. Summary of Empirical Agglomeration Research

The preponderance of evidence supports the contention that agglomeration economies significantly benefit economic performance, whether performance is measured via productivity, employment growth, innovation, or any of a number of other possibilities (Gerking 1994; Feser 1998a). Beyond the general affirmation of the importance of agglomeration economies, however, it is not easy to draw broad conclusions across the wealth of different methodologies, contexts, and industry sectors examined. The variety of empirical results is in itself an important conclusion: the effects of agglomeration economies differ widely by industry sector and by geographic

[17] Of the studies described earlier in this chapter, Pan and Zhang (2002) use firm-level data from China, Smith *et al*. (2002) from Denmark, Lehto (2007) from Finland, Chevassus-Lozza and Galliano (2003) from France, Graham (2007) and Graham and Kim (forthcoming) from Great Britain, Lall *et al*. (2004) and Kambhampati and McCann (2007) from India, Becchetti *et al*. (2007) from Italy, Hoogstra and van Dijk (2004) and van Oort (2007) from the Netherlands, Guimaraes *et al*. (2007) from Portugal, and Malmberg *et al*. (2000) and Nystrom (2007) from Sweden.

region, underscoring the crucial role of regional and industry-specific conditions in determining the influence of agglomeration. Establishment-level analyses verify the importance of firm- and plant-level characteristics as well.

There are a few tendencies observed across the empirical literature that are worth noting.[18] Urbanization and localization are for the most part too ambiguous a division to reveal consistent results, yet it does seem that localization economies are often the stronger influence in the manufacturing sector, particularly for the more mature, heavy manufacturing industries (Rosenthal and Strange 2004). Observed trade-offs between the two types of agglomeration externalities (i.e., urbanization economies are weaker for industries evidencing stronger localization economies) may be due as much to the industry classifications, however, as to distinct externality processes. Of Marshall's three agglomeration economies, labor pooling is the most commonly reported to be significant; knowledge spillovers and specialized inputs may be less straightforward to measure. Spatial proximity is essential in the process of knowledge diffusion, though the geographic spread of knowledge spillovers from industrial and public research can be quite large in extent. According to studies that take advantage of micro-level data, independent plants tend to accrue more agglomeration benefits than branch establishments, presumably because the latter can achieve equivalent or superior returns by focusing on internal or firm-level economies of scale. Similarly, small or medium-

[18] Non-empirical approaches to studying regional agglomeration are possible as well. For instance, Camagni *et al*. (1986) construct a simulation model that suggests that industrial diversity at the city level supports a higher position within the urban hierarchy. Chen (1996) features agglomeration economies prominently in his model of intraurban growth, and Fingleton (2001) presents an endogenous growth model of increasing returns to explain spatial variations in manufacturing productivity change. Such strategies ultimately must be grounded in empirical work to be useful in application.

sized establishments benefit from external economies to a greater degree than larger, more self-contained enterprises.

The great majority of empirical agglomeration studies focus on the manufacturing sector, largely in response to data limitations, but also because of the conceptual difficulty of applying the productivity framework to service and other non-manufacturing industries. A few analyses have been designed to consider the entire economy as a whole (e.g., Fogarty and Garofalo 1978; Ciccone and Hall 1996; Ciccone 2002), and some works apply the methodologies described above to non-manufacturing industries as data are available (e.g., O hUallachain 1989; O hUallachain and Satterthwaite 1992; Reynolds 1994; Combes 2000; Chen 2002; Dekle 2002; Acs and Armington 2004a; 2004b; Holl 2004a; Renski 2006). Overall, much more has been revealed about agglomeration economies as they pertain to manufacturing industries than for the remainder of the economy.

2.5. Two Key Studies of Regional Industrial Organization

Two relatively recent works aim squarely at the relationships between regional industrial organization, agglomeration, and performance, and therefore form essential precursors for this research. They do so in entirely different manners, however, making it worth examining them in particular detail.

The first is Saxenian's (1994) qualitative analysis of the regional organization of two high-technology industrial districts and the implications for sustained innovation and economic performance. Through detailed case analyses of the regional and institutional structures of the semiconductors and computers industries in the greater Boston and San

Francisco-San Jose metropolitan areas, Saxenian demonstrates the importance of factors such as formal and informal contact networks, regional industrial organization, and local institutional interactions for the creation and maintenance of positive agglomeration externalities. At the time of her analysis, the district centered around Route 128 in the Boston region constituted what she terms an independent firms system, dominated by large competitive companies with highly centralized corporate hierarchies and vertically integrated production systems. Few non-market interactions existed among firms in the industry. Loyalty, secrecy, and self-sufficiency were highly valued employee traits; the physical setting of large, self-contained, spatially separated edifices and campuses reinforced these attitudes. The most active local university in the field, the Massachusetts Institute of Technology, focused primarily on obtaining government contracts and maintaining its interactions with large firms. Buyer-supplier relationships tended to be adversarial in nature, based on lowest-cost competition, with the larger firms taking advantage of their market power over suppliers to sustain a buffer against economic fluctuations.

Silicon Valley, situated in the corridor between Palo Alto and San Jose, featured a network-based industrial system according to Saxenian. The large anchor firms in the industrial district (such as Hewlett-Packard and Fairchild) maintained decentralized and flat rather than hierarchical corporate governance structures, with loosely organized working teams and prevalent informal communication across groups. There were a wealth of independent entrepreneurial enterprises engaging regularly in both formal and informal interactions with each other, with the R&D teams of the larger companies, and with researchers at Stanford University. Firm specialization was favored over vertical integration. Experimentation and risk-taking were openly encouraged, and employees moved often from one firm to another. Many employers preferred hiring workers that brought with them the experiences and know-how gleaned from multiple previous positions. Suppliers tended to be treated as production partners and sources of feedback about market conditions instead of competitors for a limited pool of profits. The Silicon Valley region was developed more densely than Boston's Route 128, and the proximity of manufacturers supported the frequency of contacts and information exchanges. The social networks were more intensive as well, with entrepreneurs, inventors, financiers, and employees habitually communicating with each other on an informal basis. These social interactions and recurrent job switches acted as primary mechanisms for knowledge spillovers to occur among firms and research institutions in the area.

Saxenian contends that the contrasting regional industrial organizations of the two regions translated into differential innovation output, adaptability, and ultimately economic performance. The hierarchical, rigid regional industrial structure of Route 128 limited flexibility. Large firms found themselves locked in to technologies, markets, expensive equipment and other capital, and particular specialized labor skills, unable to adjust quickly to respond to shifting market conditions. Moreover, the inward focus and high degree of vertical integration made the entire district vulnerable to the fortunes of the largest firms. In contrast, the open labor market of Silicon Valley helped to develop the entrepreneurial skills of the workforce and the ability of managers to cope with rapid change. Regroupings of skills, technology, and capital arose swiftly and often spontaneously out of communications and collaborations among workers, firms, industry associations, and educational institutions, in order to meet new technical and market challenges. The fragmentation of production among large firms and numerous smaller entrepreneurial ventures yielded novel product niches. Ultimately, Route 128 proved to be the less resilient of the two industrial districts, failing to rebound from the industry decline of the 1970s, while Silicon Valley re-emerged in the 1980s as a national and international center for software and computer peripherals design and production.

Saxenian goes further, arguing that the notion of agglomeration externalities is by itself insufficient for understanding local interactions and the generation of localized productivity benefits in a region such as Silicon Valley where firm structures are flexible and interfirm boundaries are porous. The advantages of the district also involve social norms and conventions, trust relationships, and the local industrial culture, regional attributes that cannot analyzed at the level of individual firms. In other words, a regional-industrial system is not perfectly reducible into its component firms or establishments. Saxenian delineates three structural dimensions of interaction: internal firm organization, interfirm industrial structure, and overarching regional institutions and culture. This study focuses squarely on the second of these three dimensions, the organization of the industry at the regional level.[19]

Rosenthal and Strange (2003) stands as a second key antecedent of this research study. The paper explores the influence of regional industrial structure on the realization of agglomeration economies and the spatial extent over which agglomeration economies operate. Utilizing Dun & Bradstreet's *Marketplace* database, Rosenthal and Strange create indicators of industrial diversity and average establishments per worker at the zip

[19] Saxenian's line of reasoning is a major part of the impetus behind the research design of the larger project of which this dissertation forms is an integral part (see footnote 11). The combination of the modeling executed in this study with detailed qualitative case study analyses should illuminate the issues posed by regional industrial dominance along all three of the relevant dimensions.

code level for six industries: software, food products, apparel, printing and publishing, fabricated metal, and machinery. They construct concentric ring measures of localization and urbanization economies (measured as own-industry and other industry employment, respectively) at a variety of distances. Finally, indicators of industrial and corporate structure are also included: the own-industry employment measure partitioned by three establishment size categories and by plant status (independent versus subsidiary). Rosenthal and Strange estimate censored tobit regressions using two dependent variables signifying entrepreneurial activity, new firm births and employment in new establishments per square mile. Both models incorporate fixed effects for metropolitan areas and the non-metropolitan regions of each state.

The results of their analysis demonstrate that localization effects tend to be important at short ranges, but differ markedly in magnitude across industries. For all industries, the benefits of localization attenuate rapidly within the first few miles, thereafter continuing to diminish but much more slowly with increasing distance. The estimates of urbanization economies are smaller than for localization, but vary in magnitude and direction both with respect to industry sector and distance. Industrial diversity supports new firm births and employment, a result consistent with previous studies. Larger ratios of establishments to workers in the study industry yield greater values of the dependent variables, but the ratio of establishments per worker in other industries carries a negative association. As for regional industrial organization, localization benefits arising from nearby small firms (those fewer than 25 employees) are greater than from medium-sized or large firms, suggesting that a more competitive environment yields entrepreneurial advantages. There is no consistent pattern across industries concerning localization economies from independent versus branch plants. Rosenthal and Strange extend past research in the direction of this study by focusing specifically on the intra-industry aspects of industrial organization and by modeling entrepreneurial activity within a framework incorporating spatially attenuating agglomeration effects.

2.6. Summary

This chapter reviewed two branches of literature with particular relevance to the topic of regional industrial dominance. Research in the industrial organization field demonstrates that though there are observed regularities, firm size distributions and the observed relationships between industrial structure and performance differ substantively across industries and by level of aggregation. This empirical conclusion supports conducting an analysis of regional industrial dominance at the regional scale and on an industry-by-industry basis. The inherent problems associated with modeling firm size distributions suggest using summary measures to indicate regional industrial structure.

Studies of agglomeration economies have produced an exceptionally wide range of results. This may have as much to do with ubiquitous data shortcomings and the inadequacy of classifications of types of agglomeration economies as with actual empirical diversity. Many recent analyses, particularly those taking advantage of micro-level data, have turned from broad proxies toward more explicit indicators of particular localization economies. One key result produced is that agglomeration effects diminish substantially across space even at the intraregional scale.

The concept of regional industrial dominance combines elements of industrial structure with the local external environment of the firm. Therefore, agglomeration theory, able to explain industrial organization and behavior at both the establishment and regional levels, offers the most appropriate and useful theoretical structure in which to ground an investigation of the topic. The next chapter presents the conceptual framework for this analysis, elucidating the specific relationships hypothesized to exist among regional industrial dominance, agglomeration economies, and establishment performance.

CHAPTER THREE: CONCEPTUAL FRAMEWORK

3.1. Introduction

Two of the trends in the literature identified in the preceding chapter are the movement toward the explicit delineation of the causes of agglomeration advantages and the continuing separation of the concepts of industrial structure and agglomeration economies in empirical research. This study embraces the former trend while at the same time seeking to bridge the distance that defines the latter tendency. The current chapter translates the ideas presented in the context of the literature review into a theoretical framework to support and direct empirical research that has at its center the interaction of regional industrial dominance with agglomeration economies. The ways in which regional industrial dominance may affect firm performance are considered in terms of theoretical arguments and associated empirical findings. The closing section presents a conceptual diagram that places the relationships to be examined in this analysis within their surrounding context.

3.2. Regional Industrial Dominance and Firm Performance

Implicitly working within the Marshallian agglomeration economies tradition, Chinitz (1961) identifies three pathways by which the regional industrial context affects firm performance: the propensity for taking risks, the availability of specialized inputs and services, and the availability of capital. Although Chinitz does not clarify which regional characteristic in particular—i.e., industrial diversity, average establishment size, regional economy-wide dominance, or regional industrial dominance—is the intended framework for each idea, each of the three issues applies to the specific context of regional industrial dominance.[20] These three pathways form the basis for the conceptual outline at the end of this chapter and the research design presented in Chapter Four.

3.2.1. Risk-Taking

The first of the three ways in which regional industrial dominance may impact economic performance is by reducing risk-taking behavior. Chinitz suggested that the inclination of would-be entrepreneurs to take risks may be weakened in the presence of large, profitable industry leaders that offer stable and lucrative employment. In contrast, a competitive industrial environment encourages risk-taking, and along with it entrepreneurial activity and the in-migration of entrepreneurs from other industries and regions.

Subsequent authors have extended this relationship. Individuals trained in large, stable enterprises are less likely to possess skill sets suited to establishing new businesses than those previously involved in small, entrepreneurial ventures themselves. A competitive industry environment is more conducive to developing general business savvy and honing skills relevant to entrepreneurial activities in related or supporting industries (Blair 1978; Booth 1986; Sorenson and Audia 2000). Large firms are more stable, and also generally offer greater compensation, benefits, and job security, reducing

[20] Industrial diversity is the extent to which a region contains a varied mix of types of economic activities. Regional industrial dominance is defined in section 2.2 as the degree to which the economic activity of a particular industry within a region is concentrated in a single or small number of firms. In contrast, regional economy-wide dominance refers to a small group of firms accounting for a large proportion of all regional economic activity. The notion of average establishment size is straightforward.

the incidence of career displacements that provide a common impetus for individual entrepreneurialism (Mason 1991; Davis *et al.* 1996b; Ettlinger 1997; Wagner 2004; Hu *et al.* 2005). Malecki (1994) notes that entrepreneurial activities are more likely to take place in industries possessing low entry barriers, requiring minimal prior experiential knowledge, and providing greater opportunities for success. An environment of small, independent establishments is more supportive of entrepreneurial networks, group learning, and other entrepreneurial activities than a setting dominated by a small number of large firms (Porter 1990; Malecki 1994; Acs 1996; Carree and Thurik 1999; Enright 2000; Gordon and McCann 2000; Schmitz 2000; Helmsing 2001). Regional social organizations and culture help to determine support for business risk-taking, and are shaped partly by the presence of or degree of corporate dominance within regional industries (Norton 1992; Rosenfeld 1996).

The propensity for risk-taking relates to innovation and the adoption of innovations within enterprises—the creation and diffusion of knowledge—as well as to the establishment of entrepreneurial ventures. The determinants of innovative activity and knowledge exchange have formed a major research topic in recent years, revealing implications of regional industrial organization for economic development (Camagni *et al.* 1986; Glaeser *et al.* 1992; Norton 1992; Saxenian 1994; Malmberg 1996; Capello 2002a). Porter (1990; 1998; 2000; 2002) argues from the industrial organization perspective that new business formation is essential for rivalry, which in turn is crucial in providing the impetus for innovation and improvement as a survival criterion. (Porter discusses these ideas in a national context, but the concept extends to the regional scale where rivalry is spatially constrained.) Knowledge spillovers are thus more important in locally competitive than locally dominated environments (Scherer 1980; Malmberg and Maskell 2002), contradicting the earlier notion that innovation is favored in monopolistic settings where innovators capture more of the returns (Glaeser *et al.* 1992; Gort and Sung 1999).[21] Bureaucratic management structured to retain control over employees and maximize efficiency tends to inhibit innovation and spin-off formation (Booth 1986; Saxenian 1994). Moreover, the establishment of specialized government- or industry-led institutes and associations, which help to generate and diffuse knowledge, is more probable with numerous rival firms that attract more public attention and have less capacity than larger firms to support research functions in-house (Scott 1988b; Porter 1998).

3.2.2. Specialized Inputs

Regional industrial dominance also influences the incidence of localized externalities arising from access to specialized inputs. Not only does a region lacking in industrial diversity support only a narrow range of producer inputs and services, but large firms are usually more vertically integrated, curtailing accessible markets for specialized suppliers to serve other firms within the industry (Young 1928; Stigler 1951; Scott 1986; 1988a; Scott and Kwok 1989; Enright 1995; Porter 1998; Henderson *et al.* 2001b; Giarratani *et al.* 2007). Inputs that are purchased externally by large firms are more likely to be from nonlocal suppliers (Mason 1991). Members of the labor force, particularly workers with specialized training, tend to gravitate toward large and stable employers (Audretsch 2001). Analogously, producers of specialized inputs and services

[21] This contradiction is one motivation for testing Marshall-Arrow-Romer externalities against Porter externalities.

favor the stability of large volume contracts and attend first to those purchasers with greater buying power (Nelson and Winter 1982; Booth 1986).

In contrast, an environment with many rivalrous firms mitigates the bargaining power of individual firms and expands supply, increasing competition and thus performance and efficiency within the supplier industry or the labor market (Porter 1990; Helper 1991). To the extent that many potential buyers represent less risk to a supplier than one large buyer, there will be more incentive for entry into supply industries. Firms supplying several industries may be more willing to adapt products and services for an industry with many rivals than for a largely isolated enterprise, even one relatively large in size, due to lesser perceived risk. Public goods and specialized information are more likely to be available or tailored toward particular industry needs in regions in which an industry is competitively structured (Scott 1988b; Porter 1998; Mukkala 2004). Porter (1990) argues that potential job seekers are more likely to invest in obtaining industry-specific skills in the presence of rivalrous firms, and that the visibility of these firms helps stimulate the establishment of institutes and training centers that further support the development of specialized human capital.

3.2.3. Capital

Finally, finding adequate financing is crucial for minimizing business costs and enabling expansions. Suitable and attractive financing is more likely to be accessible for competitively structured regional industries. Contrary to the predictions of neoclassical theory, there is evidence of differences in the availability of capital across regions as well as among different industries and types of ventures (Clark *et al.* 1986; Mason 1991;

Becchetti and Trovato 2002; Beck *et al.* 2005; Klagge and Martin 2005; Sarno 2005; Gilbert *et al.* 2006). Larger traditional regional lenders may prefer the greater collateral and perceived security of larger, established firms in market segments the lenders have come to understand (Cole *et al.* 2004; Usai and Vannini 2005). The costs of informing potential lenders or investors of the soundness and potential profitability of investments are proportionately larger, often prohibitively so, for small firms or for entrepreneurial ventures (Berger and Udell 2002). In contrast, bankers and venture capitalists accustomed to entrepreneurial ventures are more accepting of and are better at assessing the intrinsic risks of business formation and expansion. Thus industry financiers are more likely to adopt conservative lending patterns in regions and industries dominated by large stable employers (Booth 1986; Mason 1991; Norton 1992). Moreover, external financing is typically more important for small firms (and absolutely essential for entrepreneurial ventures) since they have minimal capacity for internal financing from retained earnings (Clark *et al.* 1986; Berger and Udell 2002; Gilbert *et al.* 2006).

3.3. Empirical Research

Thus there are three theoretical mechanisms by which regional industrial dominance may detract from firm performance: by reducing risk-taking and knowledge spillovers, lessening regional accessibility to industry-specific supplies and inputs, and limiting the availability of financing. As mentioned earlier, empirical research performed to date concerning the three mechanisms has focused on regional characteristics other than intra-industry dominance, namely establishment size and regional industrial diversity.

At the individual firm level, small firms are typically found to be less productive than large firms, all else being equal, though it is unclear whether this outcome is due to oligopolistic collusion, scale efficiencies, or the positive correlation between age and survival (Caves and Barton 1990; Hay and Morris 1991; Martin *et al.* 1991; Caves 1992; Haltiwanger *et al.* 1999; Taymaz 2005). The LRD has been used to demonstrate that the productivity level and growth rate of subsidiary manufacturing establishments are positively related to the productivity of the parent firm (Baily *et al.* 1992; Bartelsman and Doms 2000). Some studies, on the other hand, find no substantial difference between small and large establishments in terms of production efficiency or input substitution flexibility (e.g., Nguyen and Reznek 1990; Nguyen and Streitwieser 1999; Nguyen and Lee 2002), or report that firms with greater market power are less productive (Nickell *et al.* 1992; Klette 1999).

Early empirical work tended to support the traditional Schumpeterian hypothesis that large organizations with greater R&D capacity will have greater innovation rates (per employee or per dollar of R&D expenditure) (Schumpeter [1942] 1950). The consensus formed over the last thirty years of research is that small and large firms contribute to innovation in different ways that depend on industry-specific characteristics and conditions (Scherer 1980; Cohen and Levin 1989; Audretsch 1995; Carree and Thurik 1999; Audretsch 2001; Gordon and McCann 2005; Therrien 2005; Chang and Robin 2006; Huergo 2006). Large firms are more likely to be early adopters of new technologies (Benvignati 1982; Rees *et al.* 1984; Dunne 1994; Harrison *et al.* 1996; Shapira and Rephann 1996; Bergman *et al.* 1999; Kelley and Helper 1999; Bergman and Feser 2001; Chen 2005).

A few studies in the industrial strategy and ecology literature support the importance of relative size, as opposed to absolute firm size, as a positive influence on business performance outcomes. Bothner (2005) finds relative size has a positive impact on sales growth in the U.S. computer industry. Survival rates of American breweries and of automobile firms in the United States, United Kingdom, France, and Germany are negatively associated with size differences with respect to competitor firms (Hannan *et al.* 1998; Carroll and Swaminathan 2000; Dobrev and Carroll 2003). From the perspective of an individual firm, larger size relative to direct competitors augments economic performance even controlling for overall industry concentration.

At the level of regional industries, smaller average establishment size is positively related to the availability of suppliers and qualified labor; outcomes of risk-taking, such as the creation of innovations, capture of knowledge spillovers, technology adoption, and entrepreneurial start-ups; and efficiency and firm growth (Blair 1978; Acs and Audretsch 1990; Audretsch 1995; Harrison *et al.* 1996; Fritsch and Lukas 1999; Kelley and Helper 1999; Fritsch and Meschede 2001; Chevassus-Lozza and Galliano 2003). For example, in regional European industries, smaller shares of large firms result in greater value added (Carree and Thurik 1999). Combes (2000) reports that larger average plant size detracts from regional employment growth in French manufacturing and service industries, and Nystrom (2007) finds that average plant size dampens the rate of firm births as well as deaths in Sweden. In the United States, average establishment size is negatively related to firm births (Armington and Acs 2002; Acs and Armington 2004b; Lee *et al.* 2004), household income (Shaffer 2002; 2006a), and employment growth (Shaffer 2006b; Loveridge and Nizalov 2007). There are some contrary indications as well. According to

Acs and Armington (2004a), greater average establishment size is associated with faster regional employment growth. In Texas, mean establishment size is positively related to new firm formation rates (Sutaria and Hicks 2004). Acs *et al.* (1999) find that industries in which employment is more highly concentrated in large firms tend to have greater productivity growth, but they cannot distinguish the effect as an inherent productivity advantage of large firms as opposed to survival bias.

Similarly, greater regional industrial diversity supports a number of desirable outcomes, including employment, firm formation, wage growth, patenting, regional stability, the transfer of beneficial spillovers, and productivity and population growth at the city and regional levels (Thompson 1974; Blair 1975; Scherer 1980; Begovic 1992; Friedman 1995; Henderson *et al.* 1995; Bostic *et al.* 1997; Quigley 1998; Holmes 1999; Hanson 2001; Armington and Acs 2002; Capello 2002a; Audretsch 2003; Henderson 2003; Rosenthal and Strange 2004). Many studies have found unemployment rates and regional employment instability to be moderated by heterogeneous regional industrial composition (among them Conroy 1975; Brewer 1985; Garcia-Mila and McGuire 1993; Malizia and Ke 1993; Hunt and Sheesley 1994; Wagner and Deller 1998; Mizuno *et al.* 2006; Trendle 2006; see Dissart 2003 for a review). As mentioned in section 2.4.2.3, Glaeser *et al.* (1992) and Feldman and Audretsch (1999) demonstrate employment growth and the introduction of innovations, respectively, to be supported by local industrial diversity. These relationships hold for industrialized nations around the globe. In France, Combes (2000) finds greater diversity supportive of employment growth. Unemployment rates are lower and per capita personal income tends to be higher in U.S. states with greater industrial diversity (Izraeli and Murphy 2003). Chen (2002) reports employment and wage growth positively related to diversity in Taiwanese cities. A diverse regional employment base is associated with a higher patenting rate in Sweden (Andersson *et al.* 2005).

The role of capital availability has not been investigated separately in these empirical analyses of regional characteristics. The main reason for this research gap is the paucity of reliable data on financing accessibility. Regional capital availability generally has been examined only with surveys or case studies of limited geographical extent. For example, Saxenian (1994) describes Silicon Valley venture capitalists as regularly engaging with local entrepreneurs, both in regard to business management and in social settings, and posits that their hands-on approach and familiarity with local entrepreneurs in the semiconductors industry led to their favor for investments in local entrepreneurial enterprises. Becchetti and Trovato (2002) demonstrate that small and medium-sized Italian manufacturers receiving grants or soft loans experience higher than average employment growth, whereas those that report credit rationing grow more slowly than the average. A few studies explore the differential accessibility of capital. Smaller and newer businesses are less likely than large, established firms to gain credit approval, particularly from large banking institutions (Berger and Udell 2002; Cole *et al.* 2004; Hyytinen and Vaananen 2006). Innovative small businesses may be at a disadvantage in obtaining bank loans (Freel 2007). Smaller regional lenders are more likely than large corporate financial institutions to use information gleaned from personal interactions and relationships over time to assess credit risks (Berger *et al.* 2002; Cole *et al.* 2004; Usai and Vannini 2005). Mallett and Sen (2001) exploit a survey database of Canadian small business loans to verify that local lending markets with greater competition do feature reduced rates.

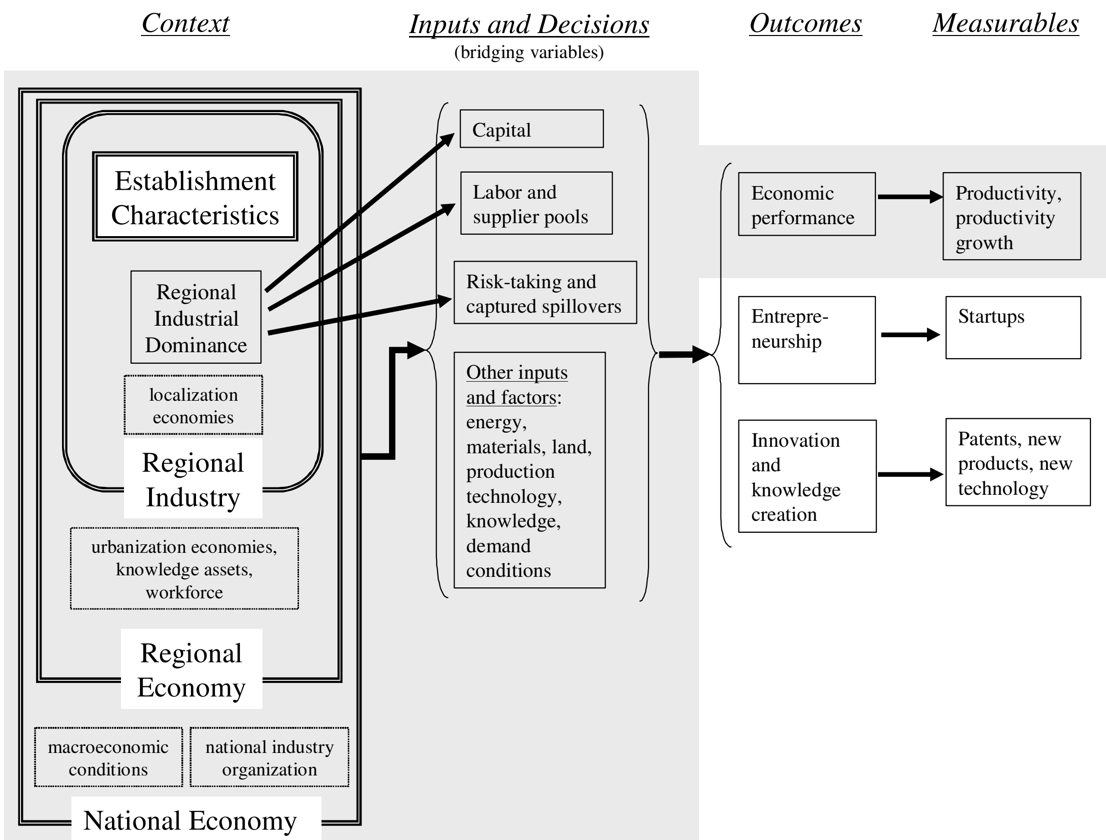
3.4. Conceptual Diagram

To model the mechanisms identified by Chinitz in a quantitative manner, firm performance must be considered in terms of specific, measurable outcomes. The possibilities include direct economic performance (e.g., productivity, growth), the creation of knowledge and innovation, and the generation of entrepreneurial activity (e.g., business startups). As illustrated by the empirical literature reviewed in Chapter Two, additional relevant outcomes do exist, but these three categories contain the most common and useful measures of firm performance.

Figure 3.1 diagrams the conceptual framework for this research study, emphasizing the theoretical linkages among variables that are of the most direct interest. The figure is a stylized representation, not exhaustive in its detail but rather intended to reflect the thought processes underlying the research design. The shaded portion of the diagram indicates the focus area for this research.

Business establishments are situated within several layers of context or environment that affect performance, displayed in Figure 3.1 as concentric rectangles. First, there are characteristics specific to the establishment. Industry features at the regional level, in particular localization economies and regional industrial dominance, play a role in firm performance. Urbanization economies operate at the level of the regional economy, interacting with other elements such as the workforce, available knowledge assets, and public infrastructure and institutions. Macroeconomic conditions

Figure 3.1. The Context of Firm Performance



and industrial organization operate at the national scale.

The outcomes of establishment activity, mediated by the economic environment at different levels of aggregation, are economic performance, entrepreneurial activity, and the creation of knowledge. These are operationalized as productivity, startups, and innovative outputs, respectively. Establishment decisions, specifically those concerning inputs and production techniques, form the link between contexts and outcomes. Regional industrial dominance is hypothesized to influence economic activity through limiting the possibilities for firms to take advantage of agglomeration economies—capital availability, labor and supply pooling, and risk-taking—otherwise supported by regional and national economic conditions and establishment-level traits.

This study focuses specifically on analyzing the outcome of productivity. The use of a production function estimation framework, focusing attention on the inputs into performance at the establishment level, makes it possible to ascertain the impacts of regional industrial dominance on productivity in a quantitative manner. Measures of potential regional agglomeration economies are included in the production model to estimate the extent to which regional industrial dominance affects the abilities of firms to improve their productivity by taking advantage of local and regional agglomeration economies. Other outcomes likely affected by regional industrial dominance and agglomeration economies, in particular innovation and entrepreneurial activity, may be explored in future research on the topic. The next two chapters present the details of the empirical methodology.

CHAPTER FOUR: MODELING FRAMEWORK

4.1. Introduction

Chapter Three developed a theoretical framework situating the concept of regional industrial dominance in relation to localized external economies and other influences on firm performance. This chapter adjoins the economic and statistical framework used to conduct the empirical analysis. There is a long history of empirical research involving production functions and related methodologies. The first two sections elaborate on the different techniques that have been developed to investigate productivity, paying close attention to the advantages and shortcomings of each approach. The remainder of the chapter describes the research design in detail, including assumptions, modeling advantages, and potential validity concerns.

4.2. Productivity Research Designs

Productivity is an obvious and natural starting place for examining regional industrial dominance, presenting perhaps the most straightforward approach for assessing the effects of regional and industry characteristics on (optimal) production decisions (Rosenthal and Strange 2004). Production theory provides a natural link between regional factors such as agglomeration economies or industrial dominance and establishment- or firm-level performance. Furthermore, economic production theory grounds empirical analysis in a strong theoretical framework. This section describes the major research designs employed in productivity analyses.

Production function studies start with the economic theory of production, relating inputs to outputs via rational profit maximization, to provide a structure for examining the influence of agglomeration economies or other factors on industry output. Although the production function label sometimes is applied to alternative outcomes, most notably the production of knowledge or innovation (Griliches 1979; Jaffe 1989; see also section 2.4.2.4), such analyses do not belong in the same methodological class because economic theory does not dictate particular relationships between inputs and production for these outcomes. "Production functions" for these alternatives typically are specified in a form convenient for regression analysis, usually a linearly additive equation, perhaps with a slight modification to include interaction terms. As mentioned earlier, alternative outcomes hopefully will be the focus of future research on this topic of regional industrial dominance.

4.2.1. Aggregate Production Functions

The empirical literature that uses production functions to examine agglomeration economies along with other influences on productivity is vast (see reviews in Moomaw 1983a; 1988; Gerking 1994; Feser 1998a; Rosenthal and Strange 2003). Most of the studies can be categorized into one of four broad methodological categories: aggregate regional production functions, establishment-level production functions, changes in productivity over time, and production frontiers. The first of these research designs utilizes publicly available regional data to estimate production functions at the aggregate industry level.[22] Industries are defined most often at a level of aggregation equivalent to one- or two-digit SIC codes.

One way to introduce agglomeration economies within an industry-level production function is to estimate a returns-to-scale parameter. This approach, employed by Shefer (1973), Carlino (1979), and Begovic (1992) among others, relies on the questionable assumption of constant returns at the establishment level, so that returns to scale greater than unity across an industry indicate positive external economies in production. The method has produced few interesting results since industry-wide returns usually have been found to be constant or nearly constant (Ke 1992).

The more common modeling approach is to consider agglomeration economies as exogenously shifting the industry production function. With a production function expressed in general form as

$$Q = g(Z) \cdot f(X) \tag{4.1}$$

where Q is output and f is a production function with argument vector X, the parameter g is a shift in productivity (sometimes called an efficiency parameter) due to factors Z other than standard inputs, such as agglomeration economies. Factor demand or cost share functions derived from the particular production function can be estimated simultaneously with the production function. This procedure improves the information efficiency of the estimates, but carries the drawback of added complexity, requiring greater sample sizes (Christensen and Greene 1976; Ray 1982; Berndt 1991; Feser 2001a).

[22] In addition to the reasons outlined in section 2.3, wide differences in the determinants of productivity and the patterns of intra-industry linkages across both industrial sectors and localities confirm the importance of modeling individual industries separately and on a regional basis (Mason 1991; Rigby and Essletzbichler 2000; Feser and Sweeney 2002; Rosenthal and Strange 2004; Kenney and Patton 2005).

The variables contained in the vector *Z* are usually assumed to enter in a Hicks-neutral manner, i.e., not affecting the relative levels of the different standard inputs into production. In contrast, factor-augmenting terms that alter the ratios of standard production inputs appear in the vector *X* or are otherwise interacted in the model with the standard inputs contained in *X*. The Hicks neutrality of external factors to production is advantageous for model simplicity but is not logically required; in fact, assuming Hicks neutrality denies the possibility that external factors may substitute differentially for distinct internal resources in production. Only a few previous studies have explicitly tested factor-augmenting forms of agglomeration economies. Feser (2001b; 2002) finds only occasional and relatively weak support for factor-augmenting urbanization and localization economies. On the other hand, Calem and Carlino (1991) find that technical progress is more highly labor-augmenting in larger cities, Martin *et al*. (1991) report that the urbanization level substantially alters estimated input substitution ratios in the meat products and household furniture sectors, and Lall *et al*. (2004) reject Hicks neutrality considered jointly for several measures of urbanization and localization economies for seven of nine industries examined. Graham and Kim (forthcoming) report that agglomeration, measured with an indicator similar to that typically used to indicate market potential, is mainly labor-augmenting but has varying effects on capital.

There are two major methodological problems encountered in estimating industry production functions. The first applies generally to the use of aggregated data: susceptibility to the ecological fallacy of inferring conclusions about plant or firm behavior from industry-level attributes. This fault is frequently labeled "aggregation bias" in the production function literature. Moomaw (1998) investigates empirically the extent of aggregation bias in regional industry production function studies by comparing the results from pooling industries at the two-, three-, and four-digit SIC levels. Finding very little difference among the sets of results, he concludes that aggregation bias does not appreciably distort the research. Without access to data at the establishment level, however, Moomaw's conclusion must be limited to comparisons among different levels of industry aggregation and cannot illuminate the extent of aggregation bias common to all studies using aggregated industry data. A series of analyses of plant-level information shows that there is substantial heterogeneity in production technology, one of the possible causes of aggregation bias, within selected manufacturing industries defined at the relatively detailed four-digit SIC level (Rigby and Essletzbichler 1997; Essletzbichler *et al.* 1998; Rigby and Haydamack 1998; Essletzbichler and Rigby 2005a; 2005b; Rigby and Essletzbichler 2006).

The second primary obstacle in conducting aggregate regional production function estimations is the lack of industry-specific capital data at the regional scale. Estimating a production function in a straightforward manner requires quantitative information concerning the conventional production inputs. Unfortunately, data on capital stock typically are not available at the regional level in the United States.[23] There are five solutions to this dilemma found in the literature, each with its attendant flaws. One strategy is to allocate a national capital figure to regions (Domazlicky and Weber 2006). For example, Munnell (1990) apportions U.S. manufacturing capital by state

[23] Capital data do exist at the regional level for some nations. For instance, Lee and Zang (1998) estimate the productivity of South Korean cities and Nakamura (1985) and Dekle (2002) examine productivity and productivity growth in Japanese prefectures using publicly available information on regional capital. Mukkala (2004) analyzes the relationship between agglomeration economies and regional manufacturing productivity in Finland. Bostic *et al*. (1997) make use of capital data that were collected for U.S. cities for the decade of the 1880s as part of the *Census of Manufacturers*.

gross book value, Garofalo and Yamarik (2002) use income estimates, and Cadot *et al*. (2006) employ a series constructed by partitioning the national capital stock by regional corporate tax rates. Aside from its relative crudity, this method can only account for differing regional industry mixes to the extent of industry disaggregation for which the allocation variable is available.

Another response is to construct a regional capital measure from the data that do exist. Nicholson (1978) calculates a measure of capital from gross capital stock and leased plant and equipment figures contained in the 1957 *Annual Survey of Manufactures*. Unfortunately, these data items are not published in later *Surveys*. Hsing (1996) instead tabulates the total current value of structures and equipment, a measure that does not account for past capital investments. A number of researchers use perpetual inventory accounting to calculate capital stock from depreciated investment streams (e.g., Segal 1976; Hulten and Schwab 1984; Fogarty and Garofalo 1988; Sveikauskas *et al.* 1988; Arayama and Miyoshi 2004; Audretsch and Keilbach 2004; 2005).[24] This technique requires detailed industry knowledge or rules of thumb to calculate appropriate industry-specific deflators and technical change rates (Moomaw 1983a), and tends to encounter multicolinearity problems (Henderson 1986). In addition, the approach assumes a uniform starting point (usually zero) at the beginning of the stream of investment data and thus may incorporate a bias against regions, most likely older industrial areas, that contain substantial initial capital stock (Moomaw 1981a; Harrigan 1999). More unusually, in a cross-sectional comparison of the United States with Brazil,

[24] Studies that use methodologies other than aggregate production functions may also apply perpetual inventory calculations to estimate capital (e.g., Luger and Evans 1988; Beeson and Husted 1989; Essletzbichler *et al.* 1998; Rovolis and Spence 2002; Cohen and Morrison Paul 2005).

Henderson (1986) proxies capital costs with the driving times to regional market centers (major urban areas).

A third tactic, employed in early work by Shefer (1973), Kawashima (1975), Sveikauskas (1975), and Fogarty and Garofalo (1978), and more recently by De Lucio *et al*. (2002), avoids the need for capital stock data by relying upon the highly suspect assumption of an identical capital-to-labor ratio across regions for each industry (Gerking 1994).[25] This assumption is probably more reasonable as engaged by Aji (1995) at the intrametropolitan level. Moomaw (1983b; 1988) and Yilmaz *et al*. (2002) adopt a fourth method, treating the capital input into production as the residual after accounting for labor inputs. Specifically, the proxy for capital is value added less payroll costs. In his 1988 study, Moomaw exchanges the dependent and independent variables in the production function to regress the labor-to-capital ratio against output, arguing that it is better to place an imperfect proxy on the dependent side of the equation.

The fifth solution for the issue of unavailable capital data is to rearrange the production function equation or take advantage of side relations derived from the production function to allow the replacement of the capital term with an indirect capital measurement. For instance, Moomaw (1981a) and Tabuchi (1986) adopt an additional equilibrium condition of equal profits across different size cities. Aberg (1973) and Moomaw (1981b; 1985; 1986) take labor productivity to be the outcome variable in the production function, and proxy the rearranged independent variable, capital intensity, with value added per labor unit (more precisely, non-labor costs per worker hour). Moomaw (1983a) notes that most of the proxies for capital intensity used in the literature

[25] Fogarty and Garofalo (1978) include a dummy variable indicating cities with over 30 percent of earnings from the manufacturing sector as a rudimentary adjustment for differences in capital-to-labor intensity.

depend upon the assumption of constant prices and rates of return to capital across regions. Moreover, he argues that the use of proxies for capital intensity or other independent variables implies stochastic measurement error, and thus can lead to errors-in-variables bias. Instead of estimating the production function itself, Carlino and Voith (1992), Lobo and Rantisi (1999), and Graham and Spence (2000) model a derived aggregate labor demand equation that assumes that (observable) regional wage rates are equal to the marginal product of labor. Ciccone and Hall (1996) and Drennan *et al.* (2002) assume that capital rental prices are uniform across the United States in order to use a factor demand function to substitute price for quantity in the regional productivity specification.

While the techniques described above may provide some degree of remedy, the methodologies available for estimating regional production functions for aggregated industry groups clearly leave much to be desired. The defects of aggregate production function work have led to wide variation and low reliability of results overall (Sveikauskas 1975; Moomaw 1983a; Sveikauskas *et al.* 1988; Gerking 1994; Moomaw 1998). Aggregate production functions were estimated extensively through the 1990s, but have become less common in recent years as some researchers have been able to access micro-level data pertaining to individual firms or establishments.

A closely related methodology is to investigate cost functions. Such studies tend to focus on the cost-efficiency of production rather than on productivity itself. The selection of a cost rather than a production approach depends heavily on the data available as well as the research purpose; cost and price data usually are more difficult to obtain at the regional level than input and production quantities. Using aggregate cost functions, Luger and Evans (1988) demonstrate the existence of technological differences within industries across metropolitan areas. Boscá *et al*. (2002) investigate the importance of public infrastructure investments to regional productivity in Spain, Rovolis and Spence (2002) conduct a similar study for Greece, and Cohen and Morrison Paul (2005) study spatial spillovers in U.S. food manufacturing.

4.2.2. Micro-Level Production Functions

The alternative of plant- or firm-level production function estimation has largely supplanted the study of regional industry production functions, despite the fact that the only comprehensive and reliable sources for relevant micro-level data in the United States are confidential, with relatively few researchers able to obtain convenient and continued access. The primary reason for the recent dominance of micro-level research designs is that many of the drawbacks of aggregate production function work, in particular aggregation bias and the lack of capital data with its associated econometric concerns, can be overcome with the appropriate application of micro-level data (Davis *et al.* 1996a; Essletzbichler and Rigby 2002; Feser 2002; Graham and Kim forthcoming). Clearly, the use of establishment-level data eliminates aggregation bias as a potential problem. Capital data often are available for individual plants in confidential datasets, obviating the need for unreliable allocations or clever but suspect work-arounds. The potential for endogenous production input quantities or prices is reduced in the context of individual establishments possessing limited market power (although there are additional endogeneity concerns; see section 4.7).

An additional argument sometimes made against industry-level production function studies is that the estimation procedures invoke the assumption of profit maximization to make inferences about the production technology from observed data, and that in turn relies upon either input prices or quantities being fixed (in order to derive first-order conditions that allow for an analytical solution) (Sveikauskas 1975; Ke 1995). The profit maximization assumption cannot be avoided in either aggregate or establishment-level production function studies, and indeed it incorporates additional structural definition based on microeconomic theory that improves estimation power. Nevertheless, profit maximization perhaps is a more reasonable presumption for individual firms or establishments than for entire industries, particularly for those plants engaged in manufacturing or other production and processing activities in all but the least established sectors.

Finally, whereas aggregate regional production function studies necessarily have to limit spatial exploration of agglomeration effects to the interregional context, research using micro-level data can incorporate intraregional spatial variation into measures of potential agglomeration economies. Some authors have taken advantage of micro-level data in this manner (Feser 2001a; 2001b; 2002; Henderson 2003) but the approach remains the exception rather than the rule.[26]

Several establishment-level production function analyses that use the *Longitudinal Research Database* to study agglomeration economies were described in section 2.4.2. Martin *et al.* (1991) compare urban and rural locations for productivity of

[26] Rosenthal and Strange (2001; 2003) model spatial variation in agglomeration economies at the zip code level and Hoogstra and van Dijk (2004), Rice *et al*. (2006), and Rosenthal and Strange (2006) calculate agglomeration measures pertaining to a series of concentric distance or travel-time rings. None of these studies involves a production estimation context.

meat packing and household furniture manufacturers. Establishment size does affect production technology but not efficiency in five selected four-digit SIC manufacturing industries (Nguyen and Reznek 1990). Feser (2001a; 2001b; 2002) examines both urbanization and localization economies as well as more specific Marshallian agglomeration economy indicators, whereas Essletzbichler and Rigby (2002) and Rigby and Esslitzbichler (2002) relate agglomeration economies, industry mix, and plant entry and exit to labor productivity. Black and Henderson (1999) and Henderson (2003) focus on distinguishing Marshall-Arrow-Romer from Jacobs externalities. Additional LRD examples investigate productivity influences ranging from workplace practices to internal R&D activity to heterogeneous labor quality to pollution abatement efforts (Nguyen and Reznek 1990; Adams and Jaffe 1996; Nguyen and Streitwieser 1999; Black and Lynch 2002; Nguyen and Lee 2002; Shadbegian and Gray 2003; Hellerstein and Neumark 2004; Moretti 2004). Ke (1995) estimates plant-level production functions from micro-level data obtained by mail survey. With data compiled from CompuStat, Melville *et al*. (2007) research the impact of information technology on firm-level productivity. Production studies are conducted with micro-level data from other nations as well.[27]

4.2.3. Changes in Productivity Over Time

One of the theoretical drawbacks of estimating cross-sectional production functions is that the approach implicitly makes the strong assumption that short-run deviations from equilibrium are uncorrelated with the independent variables. In other

[27] Sveikauskas *et al*. (1985) use data from Brazil to estimate production functions at the plant level; Pan and Zhang (2002) use data from China; Graham (2007) and Graham and Kim (forthcoming) from Great Britain; Lall *et al*. (2004) and Koo and Lall (2007) from India; Capello (2002b) from Milan, Italy; and Harada (2004) from Japan.

words, the differences observed across units are necessarily presumed to reflect variation in long-run equilibria (Schmalensee 1989; Nguyen and Reznek 1990). Estimating long-run production functions using panel data is one way to address this issue. For example, Marrocu *et al*. (2001) use panel data to estimate long-run national production functions for Italy between 1970 and 1994, incorporating regional and sectoral heterogeneity. This procedure requires an extensive time series, however, and it is not likely that production function parameters remain constant over a protracted period. An approach more widespread in the literature is to examine productivity change explicitly, modeling agglomeration economies and other factors as determinants of changes in productivity over time. Although productivity shifts over time still generally are interpreted as changes in long-run equilibrium positions rather than shock responses and reversions toward a stable equilibrium, the argument can be made that the interpretation is more reasonable when considering the causes of differences in productivity across multiple time periods. Nevertheless, the principal advantage of examining changes over time is that it permits a closer investigation of causal relationships.

Productivity growth is a frequent item of investigation at the national level, for which data are relatively abundant. Many studies use a measure of total factor productivity, an index that isolates the productivity effects caused by all factors other than changes in (standard) inputs (Hulten 2001). In regional analyses, productivity changes can be examined for the entire economy, or at the sectoral or establishment levels, depending on the data available. Beeson (1987b) finds offsetting influences on state-level productivity change from overall urbanization levels and the presence of large metropolitan areas. Moomaw and Williams (1991) reveal that state productivity growth is positively related to urbanization, unionization, education levels, and transportation infrastructure. Declining central city densities may account for some of the reduction in metropolitan productivity growth observed in the 1960s and 1970s (Fogarty and Garofalo 1988). De Lucio *et al*. (2002) use panel data for Spanish manufacturing industry sectors to report significant Marshall-Arrow-Romer externality effects on provincial productivity growth. Dekle (2002) uncovers evidence of mean reversion in productivity growth across Japanese prefectures in that productivity in the base year is a significant and negative predictor of productivity in the most recent year. Total factor productivity growth in Hungarian counties is strongly affected by knowledge spillovers (Varga and Schalk 2004). Other recent examples investigating regional productivity changes include Lee and Zang (1998), Serrano and Cabrer (2004), Destefanis and Sena (2005), Funke and Niebuhr (2005), Lee *et al*. (2005), and Bockerman and Maliranta (2007).

With plant-level data, changes in productivity over time can be related to establishment as well as industry and regional characteristics. Quite a number of studies adapt the LRD into a longitudinal micro-level data panel to track either labor productivity (McGuckin and Nguyen 1995; Jensen *et al.* 2000; Rigby and Essletzbichler 2000; Van Biesebroeck 2000; Nguyen and Ollinger 2002) or total factor productivity (Baily *et al.* 1992; Nguyen and Kokkelenberg 1992; McGuckin and Nguyen 1995; Bartelsman and Doms 2000; Bernard and Jensen 2001; Celikkol and Stefanou 2004a; 2004b; Syverson *et al.* 2005; Lee 2007). These studies examine a variety of influences on productivity, including exporting activity, research and development, technology choice, management quality, plant size and age, and mergers. Ke (1995) and Ke and Bergman (1995) study total factor productivity growth with plant-level responses to a unique mail survey.

Foster *et al*. (1998; 2001; 2002) and Doms *et al*. (2002) use establishment data from the Census of Retail Trade to investigate the growth both of overall and of labor-specific productivity. In other nations, Goto and Suzuki (1989) estimate the effects of R&D investment on the productivity growth of Japanese manufacturing firms, whereas Graham (2001) makes use of a financial database on British firms to track the relationship between local industry mix and total productivity growth. Nickell and his co-authors (Nickell *et al.* 1992; Nickell 1996; Nickell *et al.* 1997) relate productivity growth to local competition, debt levels, shareholder control, and financial market pressure in the United Kingdom. Okada (2005) investigates similar relationships in Japan. Sena (2004) examines knowledge spillovers with data from a small sample of Italian chemical manufacturing plants.

To date, the productivity change approach has recorded only limited success in isolating the particular influences on productivity that are of interest for this research study. Data sources with a sufficient longitudinal dimension are not easily come by, and agglomeration economies have not been the primary focus of most of the studies adopting the method, perhaps because most regional variables tend to exhibit relatively little change unless the time periods examined span multiple decades (Gerking 1994; Ke 1995; Feser 1998a; Rigby and Essletzbichler 2000). Because the LRD is not designed as a panel dataset, productivity change studies using the LRD are restricted to those plants included in successive years' surveys, severely limiting the available samples (see section 5.2).[28]

[28] Although Black and Henderson (1999) use a panel constructed from the LRD for a production model with plant-level fixed effects rather than for examining changes in productivity, their approach similarly requires plants to be included in at least two successive censuses. They report that their industry samples include eight percent of the original LRD establishments on average.

4.2.4. Production Frontiers

Finally, it is possible to estimate stochastic production possibility frontiers, rather than production functions themselves.[29] The idea is to estimate the properties of the optimal production technology rather than individual production functions. Normally, panel data are utilized to maximize the number of observations because in empirical studies the most efficient unit observed is assumed to be optimally efficient (Battese and Coelli 1988). Regional productive efficiency can then be assessed relative to this "best practice" production. Panel data are also required to avoid particular distributional assumptions and to allow the degree of technical inefficiency to be modeled independently of the mix of inputs into production.

The most thorough analysis of this type is likely the international effort described in Caves and Barton (1990) and Caves (1992) to compare production and technical efficiency across several industrialized countries. In that research as well as in most other studies, production frontiers are estimated at the national scale (e.g., Green and Mayes 1991; Harris 1991; Perelman 1995; Hay and Liu 1997; Driffield and Munday 2001; Alvarez and Crespi 2003; Dilling-Hansen *et al.* 2003; Taymaz 2005; Kim and Lee 2006; Lee and Pyo 2007; Liao *et al.* 2007; Madheswaran *et al.* 2007; Mahadevan 2007; Diaz and Sanchez 2008). Beeson and Husted (1989) model stochastic production frontiers for manufacturing for the different states in the United States across the 1959 to 1972 time period, finding that much of the variation in efficiency across states can be attributed to urbanization and industrial mix. Mullen *et al*. (1996) update Beeson and

[29] Data envelopment analysis is the nonparametric counterpart to the stochastic frontier approach. Because it is non-stochastic, data envelopment analysis captures measurement errors as well as any random fluctuations in the estimate of inefficiency; this may be why the technique has not been applied to the relatively disaggregated units of subsectors of the economy at the regional scale.

Husted's results to 1987 and add a demonstration of the importance of public infrastructure for manufacturing efficiency. Kim *et al*. (1999) also investigate public infrastructure impacts, in the context of South Korean manufacturing. For Spanish regions, Maudos *et al*. (2000) analyze inefficiency across industrial sectors from 1964 to 1993, Gumbau-Albert and Maudos (2002) examine the relationship between industrial concentration and productive efficiency, and Alvarez (2007) estimates production efficiency separately from different regional levels of technology. Tveteras and Battese (2006) study the technical efficiency of salmon farming in Norwegian regions. At the regional level, however, most applications of the approach consider the regional economy as a whole rather than particular subsectors or industries (see Puig-Junoy 2001 for a review). Moreover, apart from the study by Beeson and Husted (and the update by Mullen *et al*.), there are no other examples that focus on regional agglomeration economies. Perhaps this is because the optimality assumption and the relative efficiency framework are more suitable for the investigation of hypotheses concerning overall technical efficiency than the level of productivity resulting from industry- and region-specific production technologies. Of course, data limitations are a likely culprit as well.

4.3. Functional Forms

Production functions are most often specified in one of three standard forms: Cobb-Douglas, constant elasticity of substitution (CES), or transcendental logarithmic (translog). The Cobb-Douglas is the most restrictive of the three specifications. It can be expressed as

$$Q = A\sum_i X_i^{\gamma_i} \tag{4.2}$$

where Q is output, the X_i are production inputs, and A is a constant. Returns to scale in production are indicated by the sum $\sum_i \gamma_i$. Production function studies using the Cobb-Douglas form abound, examining the influence on productivity of factors ranging from pollution regulation to managerial skills to transportation infrastructure to the workplace environment (among the studies mentioned earlier in this chapter: Nicholson 1978; Moomaw 1985; Sveikauskas *et al.* 1985; Moomaw 1986; 1988; Goto and Suzuki 1989; Ke 1995; McGuckin and Nguyen 1995; Adams and Jaffe 1996; Marrocu *et al.* 2001; Black and Lynch 2002; Dekle 2002; Drennan *et al.* 2002; Yilmaz *et al.* 2002; Shadbegian and Gray 2003; Audretsch and Keilbach 2004; Harada 2004; Hellerstein and Neumark 2004; Moretti 2004; Mukkala 2004; Destefanis and Sena 2005; Okada 2005; Koo and Lall 2007; Melville *et al.* 2007).

The CES specification is typically written in nonlinear form as

(4.3) $$Q = B(\sum_i \theta_i X_i^{-\rho})^{-v/\rho}$$

where Q is output, the X_i are production inputs, B is a constant, and $\sum_i \theta_i$ is constrained to equal one. In this representation, the elasticity of substitution between pairs of inputs is $\frac{1}{1+\rho}$, and v is the returns to scale parameter. The CES reduces to the Cobb-Douglas form in the particular linearization with unit elasticity of substitution $(\rho \to 0)$. There are numerous examples of analyses using the CES function as well (e.g., Shefer 1973; Sveikauskas 1975; Carlino 1979; Tabuchi 1986; Moomaw 1988; Carlino and Voith 1992; Hsing 1996; Moomaw 1998; Lobo and Rantisi 1999; Viladecans-Marsal 2004).

The Cobb-Douglas and CES functions are advantageous for their simplicity, but the assumption of constant elasticity of factor substitution that simplifies these specifications may be unjustifiable, particularly in modeling the production of individual establishments (Nguyen and Streitwieser 1999). The most prominent alternative is the transcendental logarithmic production function. The translog function was originally introduced as an alternative for the generalized Leontief flexible form for specifying production functions (Berndt and Christensen 1973; Christensen *et al.* 1973), though adaptations to cost functions came soon afterward (Berndt and Wood 1975; Christensen and Greene 1976). Derived from a second-order Taylor series approximation to the unknown functional form, the translog specification imposes fewer *a priori* assumptions and asymptotically incorporates both of the Cobb-Douglas and CES functional forms (Chung 1994; Bairam 1998). The translog is flexible in that it does not require the assumptions of homotheticity, homogeneity, or constant returns to scale in production, but rather allows them to be tested in the modeling framework.[30] For this reason, the translog has become the specification of choice in econometric studies of production with sufficient sample size to support the relatively large number of terms in the translog equation (Chung 1994; Feser 2002).

The translog equation is quadratic in logarithms, so is generally written as

$$\ln Q = \alpha_0 + \sum_i \alpha_i \ln X_i + \frac{1}{2}\sum_i \sum_j \beta_{ij} (\ln X_i \ln X_j) \tag{4.4}$$

where Q is output, the X_i and X_j are production inputs, and α_0 and the α_i and β_{ij} terms are constants. The equation reduces to the Cobb-Douglas specification if the quadratic terms

[30] A functional form is defined to be flexible if it does not impose *a priori* restrictions on interactions among its arguments and thus provides an approximation to an arbitrary true function (Morrison 1993, p. 164).

(the β_{ij}) are zero. The translog equation provides a local second-order approximation of the CES specification under a more complex set of conditions. The quadratic Taylor series expansion around $\rho = 0$ of the CES specification given in equation 4.3 is equivalent to the translog equation 4.4 with the following three conditions (Hoff 2002):

$$\alpha_0 = \ln B \tag{4.5}$$

$$\alpha_i = \nu\theta_i \text{ for each } i \tag{4.6}$$

$$\frac{\beta_{ij}}{\alpha_i \alpha_j} = -\frac{\rho}{2\nu} \text{ for each } i, j \text{ pair with } i \neq j. \tag{4.7}$$

Because the translog equation contains a large number of independent variables, it is most often estimated jointly with a set of derived factor demand functions to improve statistical power (Ray 1982; Chung 1994; Teruel and Kuroda 2004) (see Appendix 1).

Many of the studies discussed earlier use translog production functions (e.g., Nakamura 1985; Henderson 1986; Sveikauskas *et al.* 1988; Martin *et al.* 1991; Lee and Zang 1998; Nguyen and Streitwieser 1999; Feser 2001a; 2001b; Graham 2001; Feser 2002; Nguyen and Lee 2002; Hellerstein and Neumark 2004; Moretti 2004; Graham 2007; Graham and Kim forthcoming). Nguyen and Reznek (1990) settle on the translog production function after testing and rejecting the Cobb-Douglas specification. In contrast, Henderson (2003) tries the translog form but finds the results nearly identical to those from a Cobb-Douglas specification. The translog form is also commonly applied to cost functions (e.g., Babin *et al.* 1982; Ray 1982; Luger and Evans 1988; Truett and Truett 2001; Adkins *et al.* 2003; Bitzan and Keeler 2003; Frank 2003; Apergis and Rezitis 2004; Fraquelli *et al.* 2004; Teruel and Kuroda 2004; Chua *et al.* 2005; Truett and Truett 2006; Arnberg and Bjorner 2007).

There are a few examples of other functional forms being employed in production or cost function studies. For example, Fogarty and Garofalo (1988) and Kouliavtsev *et al*. (2007) experiment with a variable elasticity of substitution (VES) production function, and Boscá *et al*. (2002), Lopez *et al*. (2002), and Cohen and Morrison Paul (2005) all use the generalized Leontief variable cost function. Brox (2007) combines the CES and translog forms in a hybrid specification. Hsing (1996) tests several forms for production functions for U.S. states, favoring the new CES (Box-Cox transformed) specification over the more common forms described above.

Finally, it is also possible to define the production function empirically, abandoning the properties of known functional forms in favor of improved model fit. Richardson's influential (1974b) paper relates growth in state gross product to agglomeration proxies using a simple linear regression model. In a methodologically similar manner but using micro-level data, Doms *et al*. (2002) examine the impact of information technology investments in the retail sector on labor productivity and Beardsell and Henderson (1999) analyze spatial concentration in the U.S. computer industry. The production function in Capello's study of Milanese high-tech firms (2002b) interacts measures of urbanization and localization economies with capital and labor in an otherwise linear equation. Cervero (2001) examines the empirical effects of employment density and transportation accessibility on labor productivity at the metropolitan level. Celikkol and Stefanou (2004a; 2004b) fit quadratic polynomial production functions in examining productivity growth patterns in the U.S. dairy and meat products manufacturing industries. The semiparametric methods adopted by Huergo and Jaumandreu (2004) to trace productivity change in Spanish firms over time do not require specifying a particular functional form. The choice to avoid standard production function forms is sometimes made due to the lack of sufficiently reliable data on capital or other inputs, or to escape from having to select and justify a particular functional form, but it abandons the hope of explicitly applying economic theory to explain the results obtained.

4.4. Overview of Research Design

This study analyzes productivity at the micro level using the *Longitudinal Research Database* (LRD), a confidential series compiled by the United States Census Bureau from establishment-level records. The LRD contains detailed information on establishment locations (counties), inputs, outputs, and key establishment characteristics for nearly all manufacturing plants across the United States. These data are combined with additional information from a variety of publicly available sources, creating a set of indicator and control variables at both the establishment and regional levels that includes measures of industrial dominance and potential agglomeration economies. This dataset is used to estimate cross-sectional industry-level production functions that model the relationship between industry structure, agglomeration economies, and productivity for three contrasting industries.

The micro-level data in the LRD yield numerous advantages for quantitative productivity analysis. Several of these were discussed earlier, in section 4.2.2: accessible capital information, diminished likelihood of endogenous input prices, avoidance of aggregation bias, and the potential to incorporate spatially varying agglomeration economies. In addition, the sample size available from the LRD is sufficient to support estimation with the flexible but relatively complex translog production and cost share system. Most importantly, estimating production functions with establishment-level data allows direct testing of the hypothesis that regional industrial dominance reduces the productivity of non-dominant firms by limiting their potential to take advantage of local agglomeration economies.

4.5. Production Model

The establishment-level production function is modeled as in equation 4.1:

$$Q = g(Z) \cdot f(X) \tag{4.8}$$

where Q is establishment output, f is a standard production function with argument vector X, and the function g is a productivity shift due to the argument vector Z. Four inputs into production are contained in the vector X: capital, labor, materials, and energy. The vector Z includes indicators of regional industrial dominance, agglomeration economies and spillovers, and relevant regional economic characteristics. The production function f is specified in translog form, expanded from equation 4.4 to include interaction terms between the standard inputs and the elements of the productivity shift argument vector Z:

$$\begin{aligned} \ln Q = {} & \alpha_0 + \sum_i \alpha_i \ln X_i + \frac{1}{2}\sum_i \sum_j \beta_{ij} (\ln X_i \ln X_j) \\ & + \sum_k \gamma_k \ln Z_k + \sum_i \sum_k \mathrm{I}(i,k)\lambda_{ik} \ln X_i \ln Z_k + \sum_k \sum_l \mathrm{I}(k,l)\lambda_{kl} \ln Z_k \ln Z_l \end{aligned} \tag{4.9}$$

In equation 4.9, i and j index the elements of the production function $f(X)$, k and l index the elements of the productivity shift term $g(Z)$, and the indicator functions in the last two summands allow for the selective inclusion of interaction terms. The first set of interaction terms permits external factors—the productivity shift variables contained in the vector Z—to enter the production function in factor-augmenting form. The effect of the element Z_k on productivity is Hicks-neutral if and only if $\lambda_{ik} = 0$ for each standard input i, a proposition that is tested empirically. The second set of interaction terms (implemented only with regional industrial dominance as the Z_k term) is included to allow estimation of the indirect effect that regional industrial dominance has on productivity through its influence on agglomeration advantages and to incorporate the square of dominance as an independent variable.

Following Kim (1992) and Feser (2002), a set of cost share equations are derived from the standard first order conditions representing profit maximization (see Appendix 1):

$$(4.10) \qquad S_i = \left(\sum_i \frac{\partial \ln Q}{\partial \ln X_i} \right)^{-1} \left(\frac{\partial \ln Q}{\partial \ln X_i} \right) = \frac{\alpha_i + \sum_j \beta_{ij} \ln X_j + \sum_k \mathrm{I}(i,k) \lambda_{ik} \ln Z_k}{\sum_j \alpha_j + \sum_i \sum_j \beta_{ij} \ln X_j + \sum_i \sum_k \mathrm{I}(i,k) \lambda_{ik} \ln Z_k}$$

where the S_i are the cost shares of the production inputs X_i and all other variables are as in equation 4.9. The system of equations consisting of the production function (equation 4.9) and the cost share functions (equation 4.10) are estimated jointly to improve estimation power, with additive disturbance terms appended that are assumed to follow a multivariate normal distribution with zero mean and constant covariance (Berndt 1991).[31,32] Since the cost shares sum to unity by construction, one cost share equation

[31] Feser (2002) and Graham and Kim (forthcoming) are recently published applications of this production function system in an agglomeration context.

[32] The cost shares in equation 4.10 are logically limited to the interval between zero and one and therefore cannot follow a normal distribution. The majority of analyses using a translog system ignore this problem; most of those that do consider the issue simply acknowledge that the multivariate normal distribution serves as an approximation to the true distribution of cost shares, the approach taken in this study. With sufficient sample size, the approximation should be quite close. Indeed, all of the empirical cost share estimates produced by the method in this research fall well within the unit interval at the sample means.
Alternatively, Rossi (1984) and Kim (1992) assume that the cost shares follow a logistic-normal distribution so that a transformation into logarithms of cost share ratios yields dependent variables distributed over the whole of the real numbers. Since this transformation merely exchanges one

(energy) is dropped to avoid a singular covariance matrix. The model system is estimated using iterated nonlinear seemingly unrelated regression (also known as Zellner efficient estimation) to allow for disturbances to be correlated across equations. Iterated seemingly unrelated regression estimates are asymptotically equivalent to maximum likelihood estimates and are invariant to the choice of which cost share equation to omit (Berndt 1991; Greene 2003).[33] The model is implemented with the MODEL procedure in SAS.[34]

The modeling procedure takes advantage of the flexibility of the translog form to test for homotheticity, homogeneity, and constant returns to scale, as well as the restrictions that reduce the translog specification to the CES and Cobb-Douglas forms. These are simplifications that can increase estimation efficiency, but should be justified by empirical testing rather than imposed beforehand (Kim 1992). The translog production function is homothetic if, for each standard input *i*,

$$\sum_j \beta_{ij} = 0 \qquad (4.11)$$

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assumption, the normal approximation, for the equally unlikely assumption of the logistic-normal distribution, it is not clear what advantage is gained. In addition, because the transformation enlarges the ranges of the dependent variables for the cost share equations, the numerical convergence criterion is relatively more difficult to attain for these equations, so that more emphasis is placed on the production function equation relative to the cost share equations during the estimation procedure and overall system convergence is more difficult to achieve. Nevertheless, the alternative production system with logarithmic cost share ratios was estimated for a subset of the industry-year pairs examined in this research, but the results obtained were markedly different and not credible.

[33] Translog systems are typically estimated using either iterated seemingly unrelated or full-information maximum likelihood (FIML) regression. Both procedures are invariant to the particular cost share equation omitted. FIML is somewhat less common in empirical studies because it tends to encounter greater difficulties in obtaining convergence and identifying globally optimal solutions. Preliminary testing demonstrated that the methods yield similar results for the modeling system in this study.

[34] Lall *et al.* (2004) substitute a bootstrapping approach for calculating standard errors for the standard iterated seemingly unrelated regression procedure implemented with PROC MODEL, reporting that the latter produces substantially smaller standard errors in some cases. To the author's knowledge, no other studies of translog production functions report bootstrapped standard errors.

where j also indexes the standard inputs. In other words, homotheticity is guaranteed if the sum of the four estimated parameters corresponding to the cross-input interaction terms is zero for each standard input. Homogeneity requires both homotheticity and, in addition, the conditions that

$$\sum_k \lambda_{ik} = 0 \tag{4.12}$$

for each standard input i. The production function is linearly homogeneous if the conditions for homogeneity hold along with constant returns to scale:

$$\sum_i \alpha_i = 0 . \tag{4.13}$$

From the discussion in section 4.3, the test for the Cobb-Douglas specification is whether $\beta_{ij} = 0$ for each pair of standard inputs $i \neq j$. The translog approximates the CES specification in the neighborhood around $\rho = 0$ if the terms $\frac{\beta_{ij}}{\alpha_i \alpha_j}$ are equal for each pair $i \neq j$.[35]

There are several assumptions inherent in this estimation model. First, the specification assumes that the model variables are exogenous to the production function (and factor share functions). This is reasonable in the context of plant-level observations, since establishments following the logic of profit maximization, particularly those belonging to small firms with little market power, regard output as endogenous and adjust production in response to changes in exogenous input prices (Morrison 1993; Feser 2002). As with all cross-sectional production studies, the methodology implicitly

[35] The CES test detailed here is based on an alternative specification of the translog production function and cost share system developed by Hoff (2002). With four standard inputs, there are six distinct $\frac{\beta_{ij}}{\alpha_i \alpha_j}$ terms, so the condition that each is equal to the same unspecified constant represents five restrictions.

assumes that the production function represents the long-run profit-maximizing equilibrium for the establishment. The particular derivation of the factor share equations relies upon the presumption of competitive input markets, but thereby avoids the *a priori* assumptions of constant returns to scale and Hicks-neutral technical change (see Appendix 1).

4.6. Regularity Conditions

As with other flexible functional forms, the translog specification does not automatically exhibit the properties that ensure theoretical consistency as a production function. The translog may violate two conditions that are necessary for well-behaved production functions: output increases monotonically with all inputs, and all isoquants (combinations of inputs that yield identical levels of output) are convex. Although these regularity criteria may be imposed globally, doing so destroys the flexibility of the translog form (Sauer and Hockmann 2005; Sauer *et al.* 2006).[36] Therefore, both monotonicity and convexity must be checked using the actual data as an adjunct to the estimation procedure. These regularity conditions may be evaluated at variable means, at individual data points in the sample, at predicted out-of-sample points, or for some combination of these points. Although it is best to check the conditions at each sample observation (Berndt and Wood 1975; Morrison 1993; Chung 1994; Sauer and Hockmann 2005), many translog production function analyses evaluate monotonicity or convexity

[36] Ryan and Wales (2000) describe a procedure for imposing local rather than global concavity. Although the technique guarantees concavity only at the chosen reference point, the authors claim that judicious selection of the reference point may lead to the concavity condition being satisfied at most or all other data points. In their empirical application, however, Ryan and Wales report estimation results with local concavity imposed that are nearly identical to the results obtained from the original translog production function with concavity violations, demonstrating that the local correction of a concavity violation may not have a large impact upon the estimated coefficients.

only at the sample mean point, and numerous studies fail to report on regularity conditions at all. In this study, monotonicity is checked separately for each standard input at each sample observation and at the sample mean point (which is the point of approximation). Convexity is also checked for each sample observation and at the sample means, with the inputs necessarily considered together.

Violations of the regularity conditions inevitably occur in a translog production function study using a sizable sample. Convexity in particular is more difficult to confirm with factor-augmenting independent variables because of the increased complexity of the production function. Previous empirical researchers suggest that a low frequency of violations is acceptable, though without specifying what percentage may be excessive (Nguyen and Streitwieser 1999). More importantly, the production function should be well-behaved at the point of approximation, and the parameter estimates obtained should not be construed to apply equally well to all points in the input space, but rather primarily in the neighborhood of the point of estimation where the combinations of input amounts are such that the production function satisfies the regularity criteria. Of course, caution should guide the interpretation in any case.

For calculation purposes, the monotonicity criterion is satisfied where the marginal products of the inputs are all non-negative. Convexity is guaranteed if the bordered Hessian matrix composed of the first and second derivatives of the production function with respect to the inputs is negative semidefinite (Chung 1994). Because both monotonicity and convexity are checked using estimated parameters, they are subject to statistical estimation error; therefore, an alternative tally is also reported that evaluates whether the monotonicity and convexity criteria are satisfied to within a small margin of error.[37]

4.7. Endogeneity Concerns

A challenge common to research on local externalities is simultaneity in the relationship between agglomeration and productivity (Black and Henderson 1999; Hanson 2001; Ciccone 2002; Rosenthal and Strange 2003; 2004; Koo and Lall 2007; Graham and Kim forthcoming).[38] The firms that are likely to be most productive may also be the firms that are most successful in identifying receptive and nurturing regions in which to locate (e.g., those with dense activity in the industry or a favorable corporate structure). Thus plant location may underlie observed productivity effects; the issue is sometimes referred to as location selectivity. While the problem is likely to be particularly severe in studies that focus on general measures of agglomeration economies, such as urban or industry scale, simultaneity may also affect analyses adopting more specific agglomeration indicators. Koo (2005b) addresses the issue using aggregate areal

[37] Because the partial derivatives of the translog production function are nonlinear functions of the estimated parameters, there is no practical way to estimate standard errors for them when evaluated at particular points. Instead, a rule of thumb error distance of 0.001 is used throughout to determine whether "near" monotonicity and convexity hold.

[38] The issue may be considered as a parallel of the more general problem of unobserved inputs into production or inputs selected contemporaneously with productivity shocks leading to simultaneity bias due to the correlation of regressors with the error term (Bartelsman and Doms 2000; Van Biesebroeck 2000; Ackerberg *et al.* 2005; Ornaghi 2006). This broader simultaneity problem is widely acknowledged in econometric analyses of production but generally goes unmentioned in agglomeration studies. Neither the instrumental variables nor the fixed effects approach provides a robust solution. The cost function may be estimated in place of the production function to avoid simultaneity but only if factor price data are available at the micro level. The most recent strategies impose a behavioral model, using observed input decisions (with investments or intermediate inputs as proxies) to control for unobserved productivity shocks, but invoke strong and non-intuitive assumptions and elicit serious colinearity problems. Moreover, they can only be implemented with panel datasets. At least two investigations of the issue, however, suggest that the bias introduced by endogenous inputs in production function estimation may be minimal (Griliches and Mairesse 1995; Moretti 2004). For this analysis, it is assumed that all of the model variables are exogenous to the production function; see section 4.5.

data by modeling agglomeration and spillovers simultaneously. Several authors argue that studies of new firm formation avoid the simultaneity issue since the choice of location is unconstrained by previous decisions and the existing economic environment is taken as given (Rosenthal and Strange 2003; Renski 2006; van Soest *et al.* 2006).

There are two statistical approaches available to deal with the issue of simultaneity: instrumental variables and fixed effects estimation (van Soest *et al.* 2006). Henderson (2003), in an application of LRD data similar to this research, tries both. Unfortunately, there are no powerful instruments available for plant-specific variables or even for industry scale or urbanization economies at the regional level (Van Biesebroeck 2000; Hanson 2001). Henderson tests completely exogenous metropolitan attributes such as county air quality attainment status and market potential but finds these regressors to be too weak as instruments for agglomeration economies to produce useful results. Instead, he implements a fixed effects approach in the context of a balanced panel dataset by including time-invariant dummies for plant locations (and also reports experiments with time- and region-specific dummies). This methodology remains vulnerable to the simultaneity problem to the degree that the presence of a given plant in a particular region and time period is the outcome of a profit-maximizing choice in an earlier time period (Rosenthal and Strange 2004; Ackerberg *et al.* 2005).

Neither strategy is appropriate for this analysis. The practical impossibility of obtaining effective instruments for the broad proxies of industry and urban scale, much less for specific agglomeration economies, precludes the instrumental variables approach. Although Henderson achieves some success with plant fixed effects, the tactic entails other limitations. Using the LRD as a panel data source necessarily limits the sample size significantly by excluding those plants for which data are not available in each year of the panel. By omitting short-lived establishments, the panel sample tends disproportionately toward plants belonging to relatively large firms, a fatal flaw for research focusing on issues of regional industrial structure. Furthermore, including plant-location fixed effects terms masks the effects of independent variables that are spatially rather than temporally variant.

There are several factors that mitigate the issue of simultaneity in this research. The problem is expected to be less acute than in other agglomeration studies given large sample sizes and the focus on effects pertaining to relatively small plants that are presumably more constrained in their location selection than larger establishments. By modeling the specific sources of agglomeration economies, incorporating spatial variation, rather than utilizing broad proxies, plant and regional characteristics affecting location selection that were treated as unobservables in previous empirical work are measured directly.

It is also worth exploring the extent of possible bias detected in previous research. Comparing the geographic concentration of innovation and production, Audretsch and Feldman (1996) find little difference between ordinary least squares results and a three-stage least squares regression that estimates innovation and production simultaneously. Henderson (2003) reports that the estimated effects of agglomeration economies on productivity are substantially stronger in the model incorporating plant fixed effects than with ordinary least squares, but that the estimated parameters differ only slightly between the fixed effects and instrumental variables versions. In their analysis of the relationship of British regional productivity variations with agglomeration, Rice *et al*. (2006) find that an instrumental variables model yields slightly larger coefficients and upholds the main findings of an ordinary least squares estimation. In studying coagglomeration tendencies using the LRD, Kerr *et al*. (2007) employ versions of proxies for three Marshallian sources of agglomeration economies calculated for United Kingdom industries as instruments for the same variables pertaining to United States industries at the nationwide scale.[39] They observe that the changes in the results compared to ordinary least squares estimations consist mainly of statistically insignificant increases in coefficient values and that the principal results are robust to the instrumental variables approach. Finally, Koo and Lall (2007) conduct a direct test of the extent of location selectivity bias for a selection of Indian manufacturing industries. They contrast estimates from a basic Cobb-Douglas production function incorporating several agglomeration economy measures with those from a two-stage Heckman sample selection model that starts with a conditional logit estimation of location choice. The correction factor from the first stage of the sample selection model is statistically significant for the majority of industries, and the effects of agglomeration economies tend to be overstated in the simple production function estimation compared to the two-stage model. Yet there are also indications that the agglomeration parameters are not distorted very much. None of the agglomeration economy parameters that are overestimated in the simple Cobb-Douglas production model fall outside of the 95 percent confidence interval of the corresponding estimate from the two-stage model. Moreover, for each industry considered, the rank-order of agglomeration economy effects is identical across the two models.

[39] Supposing patterns of industry coagglomeration cause rather than reflect patterns in the agglomeration economy measures for the United States, then if there are underlying reasons for industry coagglomeration that are common to both the United States and the United Kingdom, such an instrumental variables strategy will not eliminate endogeneity bias.

From these studies, it seems that simultaneity may cause bias in either direction, yet the effects may be relatively small. For this research, the possible remedies would themselves introduce validity threats more severe than the one redressed. Therefore, the statistical methodology of this analysis does not address directly the potential simultaneity between agglomeration and productivity. As with previous agglomeration research, the results should be considered with due caution.

4.8. Summary

This chapter presented the economic framework of productivity analysis and established the statistical framework used to estimate the effects of regional industrial dominance and agglomeration economies on plant productivity. There are advantages and drawbacks associated with each of the major research designs for examining productivity; these other approaches may provide avenues for complementary research on the subject of regional industrial dominance in the future. Although there are valid endogeneity concerns with regard to the methodology employed, there are no solutions available that do not raise subsequent, more problematic issues. Additional validity concerns associated with the data sources and the specific variables used in the analysis are discussed in the next chapter.

CHAPTER FIVE: CONCEPTS, VARIABLES, AND DATA SOURCES

5.1. Introduction

This chapter describes the dependent and independent variables entering the analysis and the data sources used to create them. Issues related to conceptual validity, measurement, and construction are discussed throughout. The section prior to the summary elaborates some of the particular validity concerns that arise from the choice of variables.

5.2. The *Longitudinal Research Database*

The primary data source for this research is the *Longitudinal Research Database* (LRD) of the U.S. Bureau of the Census.[40] The LRD is compiled from confidential establishment-level records collected for the quinquennial *Census of Manufactures* (CM) and the *Annual Survey of Manufactures* (ASM) and housed at the Center for Economic Studies.[41] The LRD contains detailed longitudinal information on establishment locations (counties), inputs, outputs, and other establishment characteristics for nearly all manufacturing plants across the United States. The coverage starts in 1963 and at present

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[40] See McGuckin and Pascoe (1988) and McGuckin (1990) for details of the construction and contents of the LRD. Davis *et al*. (1996a), in particular the technical appendix, contains a comprehensive discussion of issues related to the use of the LRD for employment research.

[41] The *Census of Manufactures* is collected in years ending in "2" and "7", with the exception of the first year of collection in 1963. The *Annual Survey of Manufactures* is conducted in the remaining four out of every five years.

stretches to the 2002 *Census* and the 2005 *Survey*.[42]

Because the LRD is compiled from confidential records, the use of the dataset and the release of descriptive statistics and results obtained from its analysis are strictly regulated. All of the information contained within this document has been reviewed by Census staff to ensure that no confidential data are revealed either directly or in possible combination with other publicly available information. The confidentiality restrictions and disclosure screening requirements limit the types and quantity of information possible to include in this study. In places, qualitative descriptions take the place of numerical tabulations or other quantitative information. Some potentially interesting but nonessential results are omitted.

Although the LRD includes information on all establishments in the United States reporting under a manufacturing industry code, the coverage is less complete for small establishments. First, though the CM contains information for all manufacturing plants, the smallest stand-alone plants are excused from completing the bulk of the census forms in order to ease the reporting burdens placed on small enterprises.[43] The records pertaining to these plants are designated as administrative records, and except for data derived from Internal Revenue Service and Social Security Administration records (employment, gross value of shipments, payroll, and the details of firm name and location), the information they contain is imputed from the directly reported items by applying industry averages. Approximately one third of the records in the CM in each year are administrative records (McGuckin 1990). Second, the ASM is a five-year panel

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[42] Annual coverage begins in 1972 since the first year of the ASM is 1973.

[43] The criteria for exemption from the filing requirement vary by year, industry, and payroll level, but through the 1972 Census the cutoff was generally fewer than ten employees and from 1977 to present the implied cutoff is approximately five or fewer employees (Davis *et al.* 1996a).

sample of plants with rotating membership.[44] Only large plants (normally those with at least 250 employees) are included with certainty in each ASM; the remainder of the sample is selected randomly to reduce data gathering costs and reporting burdens, with the probability of selection inversely related to establishment size.[45] Sample weights support imputations to the national industry or manufacturing sector levels, but in any given year the ASM includes less than 20 percent of manufacturing plants in the United States. Third, fewer items are asked of survey than census respondents; many of the data items collected in CM years are estimated or unavailable in ASM years.

Because this study focuses on the interactions among large and small establishments, only data from census years of the LRD are used in order to maximize sample sizes and obtain the most accurate balance among establishment sizes. Restricting the samples to LRD records collected via the CM also maximizes the degree to which the indicator and control variables are constructed from reported rather than estimated data. Three years of the LRD are included in the analysis: 1992, 1997, and 2002. Administrative records are excluded from the samples; otherwise, the analysis would tend to reflect imputation rules rather than establishment-level productivity relationships.[46] Establishments with zero reported employment are also omitted as non-active. These steps are common practice in econometric studies employing LRD information (e.g., Feser 2001b; Rigby and Essletzbichler 2002; Henderson 2003). It should be emphasized that by excluding these establishments, the results of the analysis

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[44] Each ASM panel is surveyed the two years prior to and the two years subsequent to a Census year.

[45] Prior to 1979, the unit determining selection was the firm rather than the establishment (Davis *et al.* 1996a).

[46] Administrative records are used in the measurement of regional industrial dominance; see section 5.6.

apply not to the complete study industries but rather to the subsets that exclude the very smallest producers. For brevity, the samples often are referenced as the study industries without repeating this qualification. Section 6.2 compares the resulting samples to the full set of records in the LRD.

5.3. Selection of Study Industries

The research is conducted for establishments in three manufacturing industries: rubber and plastics manufacturing (Standard Industrial Classification 30), metalworking machinery (SIC 354), and measuring and controlling devices (SIC 382).[47] The rubber and plastics industry manufactures both materials used in other manufacturing sectors and finished products made out of rubber or plastic ranging from polyvinyl chloride (PVC) pipes to automobile tires to styrofoam cups and beverage bottles. Petrochemicals are the primary raw material in the production of plastics and synthetic rubber. The larger portion of the industry's output is purchased as intermediate inputs, comprising a major input for heavy manufacturing industries including motor vehicles and aircraft.

Metalworking machinery manufacturers design and construct the equipment that is used to form metal into precision shapes, either while it is molten or in its solid phase. Metal parts have declined in prevalence and bulk with the growth of plastics as an alternative, lighter weight material, but remain essential in a huge variety of manufactured products. The metalworking machinery industry manufactures specialized

[47] Manufacturing represents a declining portion of national economic activity and employment. Unfortunately, the LRD covers only the manufacturing sector. As alluded to in section 2.4.2.6, the scope of the database is based on industrial classification templates that do not reflect the production of non-primary outputs or inter-establishment linkages such as subsidiary or purchasing relationships. Productivity estimation for non-manufacturing sectors also faces the difficulty of constructing conceptually robust input and output measures (Bartelsman and Doms 2000).

drills, molds, dies, grinders, and presses, as well as the accessories needed to maintain, repair, and customize these metalworking machines. These products are sold primarily to companies operating in other manufacturing sectors. Metalworking machinery establishments tend to be substantially smaller than plants producing specialized machinery for particular sectors such as agriculture, construction, mining, and power transmission.

The measuring and controlling devices classification encompasses a variety of outputs that involve similar production processes, including analytical laboratory apparatus, thermostats and environmental controls, meteorological instruments, fluid meters, motor vehicle gauges, aircraft engine and aeronautical navigational instruments, electrical signal monitors and testing equipment, and instruments for detecting and monitoring radiation. As with the other two study industries, most of the production of the measuring and controlling device manufacturing industry supplies other manufacturing sectors. Many manufacturers in this industry enjoy substantial military procurement contracts.

These three industries satisfy several important criteria. Each has enough establishments located in a sufficient number of regions in each of the three study years to present adequate variation in the level of regional industrial dominance and a large enough overall sample size to support the translog estimation system. Establishments in these industries have flexibility in location choice; none is closely tied to localized natural resources. The industries present a contrast between traditional, established industries producing many relatively stable, standardized products in a capital-intensive manner (rubber and plastics and metalworking machinery) and a more technology- and innovation-intensive manufacturing industry (measuring and controlling devices). Comparing results among the study industries will provide a preliminary indication of whether the impacts of regional industrial dominance differ for traditional versus technology-based industries, given that the latter are typically subject to shorter innovation cycles.

Finally, the three industry classifications are relatively homogeneous in terms of their production technologies. Cross-sectional production function modeling necessarily assumes identical production technology across establishments. Compared to other two- and three-digit SIC manufacturing sectors, the four-digit SIC components of the three selected study industries evidence relatively similar purchasing relationships nationwide.[48] Whereas industries defined at the four-digit (or even more detailed) SIC level would more closely satisfy this criterion of homogeneous inputs and production technologies, there would be too few regions with a sufficient number of establishments or too little variation in domination across regions to support robust estimations for such precisely defined industry categories. In addition, the degree to which plant-specific heterogeneity and outliers distort production estimations increases with sectoral specificity and the consequently smaller samples (Rigby and Essletzbichler 2002).

The three study industries are defined according to the 1987 version of the Standard Industrial Classification (SIC) system. This is the classification system used for the CM and LRD for 1992 and 1997. Starting with the 2002 CM, however, plants are

[48] According to data from the *Benchmark Input-Output Accounts* of the Bureau of Economic Analysis, the mean pairwise correlation of purchase vectors among the four-digit SIC subsectors within the rubber and plastics industry ranks seventh highest out of the twenty two-digit SIC industries in 1992 and fourth highest in 1997. Measuring and controlling devices ranks tenth and metalworking machinery 37th among the 79 three-digit SIC industries containing more than one four-digit component in 1992; the two sectors rank 28th and 24th, respectively, out of the 76 three-digit SIC industries reported in 1997. The 2002 data were not available publicly at the time of writing.

categorized into industries by the newer North American Industrial Classification System (NAICS).[49] Two approaches are used to identify the set of establishments from the 2002 LRD that fall within the established study industry sectors. First, the 2002 LRD is cross-referenced with the 2001 *Longitudinal Business Database* (LBD), and the SIC industry coding from the latter dataset is adopted for establishments appearing in both datasets.[50] A large majority of the plants ultimately included in the 2002 study samples are identified in this manner.[51]

Second, the remaining plants are assigned SIC codes according to a crosswalk developed from the bridge calculated by the U.S. Census Bureau by cross-classifying establishments from the 1997 CM (United States Census Bureau n.d.-a). Table 5.1 displays the crosswalk relating the three study industry SIC codes to five- and six-digit NAICS codes. The principal organizational changes introduced with the NAICS are within the services sector, so the translation for manufacturing industries is quite good. Nevertheless, because the correspondence between the two industry classification schema is imperfect even for the detailed two- and three-digit SIC levels in manufacturing, some noise is introduced into the samples in the form of establishments included that (according to the older SIC classification) should be excluded and conversely plants excluded from the sample that should be included (see also section 6.2). Consequently,

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[49] The 1997 and the 2002 versions of the NAICS are identical for the manufacturing industries used in this analysis.

[50] The *Longitudinal Business Database* is a confidential Census Bureau dataset that tracks business establishments over time and contains identifiers such as name, location, and industry (but not information on inputs and output). The LBD is constructed from the *Standard Statistical Establishment List* and is not restricted to the manufacturing sector. For more information about the LBD see Jarmin and Miranda (2002). The most recent version of the LBD available at the time of analysis is from 2001. Most of the manufacturing plants contained in the 2002 LRD are listed in the 2001 LBD.

[51] Establishments founded after the data collection occurred for the 2001 *Standard Statistical Establishment List* appear in the 2002 LRD but not in the 2001 LBD.

Table 5.1. Study Industry Definitions by SIC and NAICS Codes.

Industry	SIC	NAICS	
rubber and plastics	30	325991	32616
		326113	326191
		32612	326199
		32613	326211
		32614	32622
		32615	32629
metalworking machinery	354	332997	333515
		333511	333516
		333512	333518
		333513	333991
		333514	333992
measuring and controlling devices	382	333314	334516
		334512	334517
		334513	334518
		334514	334519

the estimations that use the 2002 samples may yield weaker results, though the degree of difference should be slight.

5.4. Regions

The geographic regions used in this study are Labor Market Areas (LMAs) as defined by the United States Department of Agriculture on the basis of 1990 Census population counts and county-to-county commuting patterns (United States Department of Agriculture 2003).[52] These are the most appropriate units available for the purpose of examining regional industrial interactions across the nation, as they are constructed from

[52] Although the LMA definitions were scheduled to be updated with 2000 Census information, the long-overdue revision remained unavailable at the time of writing. Regional definitions based on 1990 data arguably are as appropriate for this analysis in any case, being more suitable for analyzing industry production choices in 1992 and perhaps in 1997.

individual counties to approximate the boundaries of functional economic areas and cover the entire United States. The 1990 LMAs vary from single counties to amalgamations of more than 20 counties; most regions contain between four and twelve counties (see Appendix 3). Establishments in Alaska and Hawaii are excluded from the samples due to their relatively isolated locations. The samples also omit establishments in the three most populous LMAs as outliers because of those regions' size, density, and volume of international linkages.[53] Outside of these three, there are 388 LMAs in the continental United States.

5.5. Output and Standard Inputs

Establishment output and the conventional arguments of the production function and cost share equations are based on LRD information, following the methods of previous analyses using the dataset (e.g., Nguyen and Reznek 1990; Martin *et al.* 1991; Feser 2001b; 2002; Henderson 2003; Syverson *et al.* 2005). All monetary amounts contained in the LRD are reported in units of thousands of nominal dollars. Observations with non-positive calculated measures for output, capital, labor, energy, materials, or the associated cost shares are dropped from the final samples (see section 6.2).

Most productivity and industrial organization research considers production in terms of the value of output or sales. In this study, output at plant z, Q_z, is defined as the total value of shipments adjusted for inventories and work in process:

$$Q_z = TVS_z + (WIE_z - WIB_z) + (FIE_z - FIB_z) \tag{5.1}$$

[53] The three most populous LMAs contain the city centers of New York, Los Angeles, and Chicago. The removal of the ten largest LMAs (the additional seven comprise the centers of Boston, Detroit, Houston, Newark, Philadelphia, San Francisco, and Washington) yields results that are similar in qualitative terms but are weaker due to substantially reduced sample sizes.

where TVS_z is the total value of shipments, WIE_z is the value of work in process at the end of the year, WIB_z is the value of work in process at the beginning of the year, FIE_z is the end-year value of finished product inventories, and FIB_z is the value of finished product inventories at the beginning of the year.

There are four conventional inputs into the production function. The first, capital services, K_z, is the sum of the book values of capital assets and capitalized rentals:

(5.2) $$K_z = TAE_z + \frac{BR_z}{BPR} + \frac{MR_z}{MPR}$$

where TAE_z is the value of building and machinery assets at the end of the year, BR_z is the rental expenditures for building assets, MR_z is the rental expenditures for machinery for the year, and *BRP* and *MPR* are industry-specific capital prices. The latter two terms correspond to capitalized building and machinery rentals, derived by dividing the actual rental expenditures for each asset category by three-digit SIC capital prices obtained from the Bureau of Labor Statistics.[54] Although measurement of capital stock via perpetual inventory accounting arguably is preferable on theoretical grounds, the technique is viable only for firms or plants observed continually over a substantial period of time, whereas this analysis is restricted to a cross-sectional framework. Gross capital stock has been demonstrated to provide a reasonable alternative approximation in micro-level

[54] The three-digit SIC capital price information originates with an unpublished dataset consisting of national productive stocks and rental prices by detailed asset category and by year that was produced by the Bureau of Labor Statistics as part of their multifactor productivity estimation program. Industry-specific capital prices are computed by summing prices weighted by national productive stocks across asset categories classified either as buildings or machinery. The overall industry-specific capital price used in estimating capital cost is calculated similarly by combining prices across all asset categories. These data are no longer made available publicly and the dataset only extends to 1999. For the 2002 samples, capital prices were estimated in two ways: by extrapolating building and machinery capital price trends to 2002 using the best-fit linear regression based on the data for 1987 through 1999, and by simply deflating with the latest available (1999) capital prices. Since the two methods yield little difference in results, the latter method is adopted.

research using the LRD (Doms 1996; Dwyer 1997; Syverson *et al.* 2005). Capital costs, C_{Kz}, are estimated as

(5.3) $$C_{Kz} = (TAE_z \cdot CAPPR) + BR_z + MR_z$$

where *CAPPR* is the industry-specific overall capital price combining both building and machinery assets.

Labor, L_z, is measured in terms of hours:

(5.4) $$L_z = \frac{WP_z + WNP_z}{(WP_z / PH_x)}$$

where WP_z and WNP_z are production and nonproduction worker payrolls, respectively, PH_z is the number of hours worked by production workers, and thus the denominator is the average production worker hourly wage.[55] The measure of labor represents an estimate of total production-worker-equivalent hours, since the number of hours worked by non-production workers is not available directly. In the production context, this construction presumes that relative wages are proportional to marginal productivity, but unlike the direct measure of the number of employees (collected for March 12), it presents the advantages of accounting for part-time or part-year employees and reflecting labor fluctuations that occur over the entire year (Martin *et al.* 1991; Syverson *et al.* 2005). Labor cost, C_{Lz}, is

(5.5) $$C_{Lz} = WP_z + WNP_z + SLC_z$$

where SLC_z is supplemental labor costs.

[55] For a very small number of establishments with records missing the number of production hours worked, the denominator was instead taken to be the national industry-year average production wages per hour (i.e., the same construction but aggregated across all establishments in the continental United States in the industry, weighted by production employment).

Some LRD-based studies implement a production function with three standard inputs, considering energy and other inputs together as "materials" (e.g., Nguyen and Reznek 1990; Henderson 2003). The data within the LRD are sufficient, however, to separate energy from the remaining production components. The CM includes items recording the annual costs of purchased fuels and electricity as well as the quantity of electricity purchased in thousands of kilowatt-hours. Therefore, plant energy consumption, E_z, is

$$E_z = CF_z\left(\frac{1{,}000}{EPR}\right) + PE_z\left(\frac{3{,}412.705}{1{,}000}\right) \tag{5.6}$$

where CF_z is the cost of fuels, PE_z is the quantity of purchased electricity, EPR is the average cost per million British Thermal Units (BTUs) of purchased energy measured across the industrial sector by state and year, and the constant ratio in the second term translates the purchased electricity quantity from thousands of kilowatt-hours to millions of BTUs. The values of EPR come from the State Energy Data System (Energy Information Administration n.d.). Energy cost, C_{Ez}, is

$$C_{Ez} = CF_z + EE_z \tag{5.7}$$

where EE_z is the cost of purchased electricity.[56]

Lastly, materials, M_z, is the sum of remaining production expenditures:

$$M_z = CP_z + CR_z + CW_z + CPC_z + RB_z + RM_z + \left(MIB_z - MIE_z\right) \tag{5.8}$$

where CP_z is cost of materials and parts, CR_z is expenditures for resales, CW_z is the cost of contract work, CPC_z is purchased communications services, RB_z and RM_z are building and machinery repairs, and $MIB_z - MIE_z$ is the difference between materials inventories

[56] As with the labor input, the energy quantity or cost was estimated for the handful of establishments missing data on purchased electricity quantity or cost by replacing establishment-specific figures with the national industry-year average.

at the beginning and end of the year. (Decreases in materials stockpiles represent net positive amounts of materials contributed to production.) The materials input acts as a catch-all category for production-related expenses that are not classified as capital, labor, or energy. For the majority of manufacturing plants, the chief components of materials costs are parts, resales, contract work, and changes in inventories. Because materials is measured in dollars, it is identical to material cost, C_{Mz}.

The plant cost shares, S_{iz}, are the cost of each conventional input relative to the summed cost of all four inputs:

(5.9)
$$S_{iz} = \frac{C_{iz}}{\sum_i C_{iz}}$$

for $i = K, L, E$, and M.

5.6. Regional Industrial Dominance

The operationalization of regional industrial dominance is central to this study, but as the concept has not appeared in quantitative empirical research, there is no strong theoretical or empirical basis upon which to base the selection of an appropriate measure. Previous industrial organization work has sought to fit observed frequencies of establishments sizes with well-defined parametric distributions, but this approach is inappropriate for the current study for several reasons, including the likelihood of distributions varying across industries and over time and the inapplicability of standard statistical methodologies for confirming extreme hypotheses (see section 2.3).

One alternative is to turn to simpler, scalar indicators of industrial structure. A variety of summary statistics pertaining to industrial concentration or market power have been adopted in investigations conducted at the industry scale, including concentration ratios, likelihood ratios, the Gini coefficient, the Herfindahl-Hirschman index, entropy measures, and the sample variance of firm size (Needham 1978; Hay and Morris 1991; Amato 1995; Azzam *et al.* 1996; Greunz 2003b; Powell 2003; Porter and Sakakibara 2004; Powell and Lloyd 2005). As mentioned in section 2.3, summary statistics necessarily contain less information than a fully-defined distribution; this is an advantage in terms of practicality but complicates selection because individual measures offer distinct properties and thus can lead to different conclusions (Leach 1992). For example, most of the indicators listed above are absolute in the sense that they depend in some manner on the total number of observations. The Gini coefficient, however, is a relative measure, corresponding only to the degree of inequality among observations rather than their count.

Empirical comparisons conclude that no single measure is superior to the others across varied applications (Hay and Morris 1991; Amato 1995). This study considers four different dominance indicators, included separately as the measure of regional industrial dominance in different estimations of the production model.[57] Each indicator is constructed for the three study industries at the regional (LMA) level. Regional industrial dominance is calculated with reference to firms rather than plants since the hypothesized mechanisms of dominance identified in Chapter Three are most likely to operate at the level of strategic decision-making. Therefore, establishments within a region that are part

[57] An additional reason for using multiple regional industrial dominance indicators is discussed in section 6.4.

of multi-unit firms are first aggregated to the firm level.[58] The total value of shipments is adopted as the measure of firm size.[59] Because each plant included in the CM reports the value of shipments directly, administrative records are included in the calculation of the regional industrial dominance measures, ensuring that the measures of regional dominance are not skewed by the exclusion of the smallest plants from the industry samples.

Whichever indicator is used, the regional industrial dominance variable enters the production function in quadratic form (i.e., with both a linear and a squared component). This enables investigation of basic nonlinear impacts, a possibility suggested by earlier empirical work on industrial concentration (see section 2.3). Dominance is also interacted both with the standard inputs, to assess factor augmentation, and with agglomeration variables, to estimate the indirect impacts of dominance on productivity via limiting the advantages obtained from agglomeration economies.

The primary measure of regional industrial dominance in this study is a concentration ratio. The concentration ratio is an absolute measure, but is insensitive to the pattern of firms sizes that occurs at the low end of the distribution, a property that is in accord with the theoretical conception of dominance as presented earlier and is appropriate given the exclusion of the very smallest plants from the samples used for

[58] Since the LRD only contains manufacturing establishments and the aggregation only occurs within regions, the result is not necessarily full firms but rather the same-industry and same-region manufacturing components of multi-site firms. This aggregation is referred to throughout as the "firm" level for the sake of concision. As an extension of the principal analysis, the LBD is used to create alternative dominance measures that aggregate regional establishments that are part of the same firm but that may be classified into unrelated industrial sectors (see section 8.3).

[59] The total value of shipments may inflate the size of isolated firms relative to those that are more vertically integrated by including interfirm sales. This is much less of an issue, however, with micro-level data available at the establishment rather than the firm level. Other variables standardly used to indicate firm size, such as value-added, employment, or assets, carry their own drawbacks (Baily 1986; Hay and Morris 1991; Lee and Zang 1998). Tests of alternative regional industrial dominance measures based on employment instead of the value of shipments yield qualitatively similar results.

estimation. Concentration ratios are perhaps the most widely used indicator of industrial concentration, in part because they have been made available by the United States Census Bureau at the national level in public-release versions of the CM and for equivalent datasets by other nations (Golan *et al.* 1996; Cortes 1998; Kambhampati 1998).

The concentration ratio indicator of regional dominance for this analysis, D_{Crx}, is based on the five largest firms in the industry and region:

$$D_{Crx} = \frac{\sum_{y \in T} Q_{rxy}}{\sum_{y=1}^{n} Q_{rxy}} \tag{5.10}$$

where x indexes the industry, r indexes the region, y is the index for individual firms, Q represents output (the value of shipments), and n is the number of firms in the industry in the region. The set T consists of the five firms with the largest output, considered regional industry "dominators". Thus D_{Crx} is simply the ratio of output in the dominating firms to total regional output in the industry. Only establishments in regions containing at least twelve firms in the industry are included in the estimation samples, in order to ensure the meaningfulness of the concentration ratio measure.

Alternative versions of the concentration ratio were tested altering the basic parameters: the number of top firms considered dominators, the minimum number of firms in the regional industry to be included in the sample, and substituting employment for shipments as the size variable. Although the results of the estimations do vary to some degree with these changes, particularly with the altered sample sizes that follow from modifying the minimum allowable number of firms in each regional industry, the conclusions described in the following chapters are qualitatively robust to these alternative specifications.[60,61]

Other than the concentration ratio, market power is most frequently measured with indices constructed from the full set of firm size shares. Some industrial economists contend that these indices are preferable to concentration ratios because they take into account the entire firm size distribution and are sensitive to both the total number of firms and the relative distribution of size among firms; concentration ratios essentially depend on only one point in the size distribution (Hay and Morris 1991; Amato 1995). The different indices are distinguished by the ways in which they weight the size shares. The most common is the Herfindahl-Hirschman index, which weights each size share proportionately to relative firm size.

Two indices with contrasting size-share weights provide alternatives to the concentration ratio measure in this study. First, the Herfindahl-Hirschman index, D_{Hrx}, is constructed by summing the squares of each firm's share of regional industry output:

(5.11) $$D_{Hrx} = \sum_{y=1}^{n} \left(\frac{Q_{rxy}}{\sum_{y=1}^{n} Q_{rxy}} \right)^2$$

[60] In other words, models run with the alternative specifications yield figures that differ from those presented, in some cases with alterations in the degree of confidence in the conclusions reached, but that do not differ enough to invalidate or reverse the substantive findings.

[61] The overriding change observed as the number of top firms considered dominators increases or the minimum threshold number of firms in the regional industry rises is that there is a large decline in sample sizes and consequently the parameter estimates become much less significant, incapable of supporting inferences with any reasonable level of confidence. The results obtained from employment-based dominance measures are generally similar but weaker than those with the dominance variable constructed from data on shipments. Shipment value is ordinarily the more stable datum, since it is an annual total whereas employment is reported as of March 15 of the census year.

where the notation is as for equation 5.10. Because the weights emphasize the largest firms, the index is quite insensitive to the distribution of size among the smaller firms. The Rosenbluth index, D_{Rrx}, instead weights by descending firm size rank:

$$D_{Rrx} = \frac{1}{2\sum_{y=1}^{n}\left(\frac{Q_{rxy}}{\sum_{y=1}^{n} Q_{rxy}}\, y\right) - 1} \tag{5.12}$$

where y indexes the firms in the regional industry ordered by the total value of shipments and the rest of the notation is the same as for equations 5.10 and 5.11. By weighting the smallest firms the most heavily, the Rosenbluth index puts greater emphasis on the small end of the firm size distribution. Unlike the concentration ratio, these indices can be calculated for regional industries with any number of firms. Nevertheless, the same minimum of twelve firms in the industry is imposed to preserve the meaningfulness of the intra-industry regional dominance concept. The firm minimum also serves to maintain identical estimation samples across the different dominance measures. One additional index, Theil's entropy measure, was also tested, but its weighting scheme and the results obtained are both quite close to that of the Herfindahl-Hirschman index.[62]

Finally, the Gini coefficient is included as a representative of the class of relative concentration measures. The Gini coefficient, D_{Grx}, may be measured by the area under a Lorenz curve, visually indicating the extent to which the size distribution differs from equal apportionment, or may be calculated more simply via the fact that it is the relative counterpart of the Rosenbluth index (Needham 1978):

[62] Theil's entropy measure uses the natural logarithm of the size shares as weights (Attaran and Saghafi 1988).

(5.13) $$D_{Grx} = 1 - \frac{1}{n \cdot DR_{rx}}$$

where *n* again signifies the number of firms in the regional industry. The Gini coefficient is often interpreted as an indicator of the degree of inequality in a distribution. As with the other dominance measures, the Gini coefficient is only considered for those regional industries with a minimum of twelve firms.

Table 5.2 lists the four dominance measures considered in the analysis and their theoretical ranges. As with the primary concentration ratio measure, versions of the three index measures were tested that change the flexible parameters: the exponent in the Herfindahl-Hirschman formula, the minimum number of regional industry firms for sample inclusion, and substituting employment for shipments as the size variable. Again, the conclusions reached in Chapters Seven and Eight are qualitatively robust to alternative specifications.

Table 5.2. Measures of Regional Industrial Dominance.

Measure		Description	Dominance Range	
			minimum	maximum
D_C	five-firm concentration ratio	sum of size shares of five largest firms	$5/n$	1
D_H	Herfindahl-Hirschman index	sum of squared firm size shares	$1/n$	1
D_R	Rosenbluth index	sum of firm size shares weighted by descending size rank	$1/n$	1
D_G	Gini coefficient	difference from equal distribution	0	$1-1/n$

Note: *n* signifies the number of firms in the regional industry.

Each of these dominance measures is constructed to be specific to both the particular industry and the region. Additional measures of regional dominance that are not industry-specific but rather consider dominance across the regional manufacturing sector or the entire regional economy are investigated as an extension of the principal analysis (see section 8.3).

5.7. Agglomeration Economies

There are two key dimensions of potential agglomeration: geographic and economic distance.[63] Geographic distance refers to the attenuation of agglomeration benefits with spatial separation, whereas economic distance refers to the degree of linkages or similarities in production processes such that businesses may gain advantage from the presence or economic activity of other establishments. The two dimensions may be represented dichotomously or continuously, but both should be included in measuring external economies.

Indicators of agglomeration economies may be based either on size (e.g., employment) or counts (e.g., number of establishments). The measurement scale may be either absolute (e.g., for labor pooling, the number of potential workers) or relative (e.g., the percent of the accessible workforce that are potential workers) (Rosenthal and Strange 2004; Feser *et al.* 2005). In general, absolute measures are favored because they indicate the volume as well as the intensity of potential agglomeration benefits. Although it may

[63] Rosenthal and Strange (2004) identify time as a third dimension. As Renski (2006) notes, the longitudinal limitations of available datasets and the inconsistency of industry definitions and data collection practices over time make the direct examination of long-term accumulated or lagged effects of agglomeration economies very difficult. Because of these concerns, as well as the practical consideration of limiting the number of independent variables, this analysis includes only contemporary measures of potential agglomeration economies. Two historic indicators of industrial structure are included; see section 5.8.

be preferable from a theoretical standpoint to maintain consistency across measures with regard to these aspects, data limitations as well as multicolinearity problems force differences in the construction of some of the measures. Studies that examine multiple sources of agglomeration economies must accept the frustrating trade-off between individual construct strength and multicolinearity among the several constructs.[64] The difficulties intrinsic to disentangling the different types and mechanisms of external economies and spillovers present a common thread throughout the empirical agglomeration literature (Breschi and Lissoni 2001; Renski 2006). Numerous variants of each agglomeration measure were tested, with the final versions ultimately selected to maximize concept validity and variation within samples while avoiding multicolinearity issues as much as possible.

Five measures of potential agglomeration economies are included in the production model, representing possible labor pools, two types of supply pools, and two aspects of regional knowledge spillovers. The measures are conceptually similar to those employed successfully in other recent agglomeration economies research (e.g., Feldman and Audretsch 1999; Drennan *et al.* 2002; Feser 2002; Rigby and Essletzbichler 2002; Renski and Feser 2004; Koo 2005b; Renski 2006). As in other studies, the variables estimate potential agglomeration economies based on observable characteristics (Richardson 1974a). Unfortunately, there are no adequate data available both at the regional scale and on a nationwide basis with which to construct an indicator of capital or financing availability. The five agglomeration variables are interacted in the production function equation with the standard inputs to accommodate changes in factor usage and

[64] The conflict between construct validity and multicolinearity is made worse by the urban nature of the industry samples; see section 6.2.

are also interacted with regional industrial dominance in order to model explicitly the effects of dominance upon the ability of establishments to take advantage of agglomeration economies.

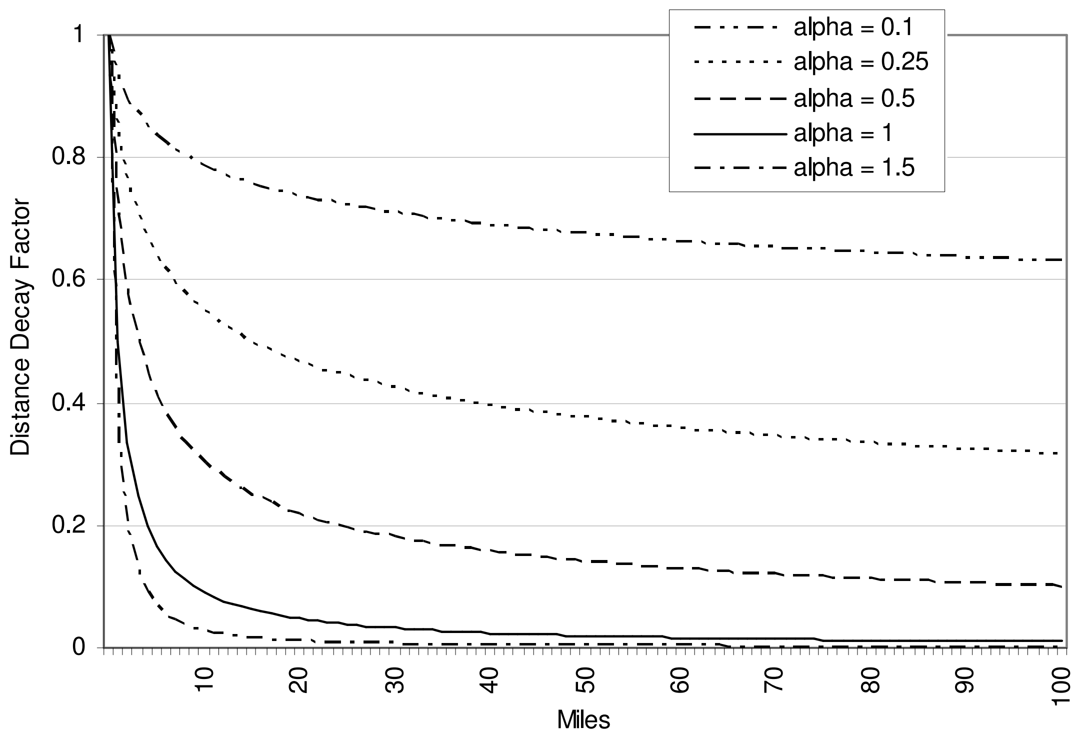
All of the agglomeration indicators are based on establishment size rather than plant counts, since the external economies being studied are dependent on the scale of productive activity rather than the precise division into economic units and are measured in the same way for establishments of different sizes. Four of the five variables use absolute measurement scales. Regional population density, included in the production function as a control, also helps to account for the absolute dimension.[65] All five of the agglomeration economy variables adopt continuous versions of economic distance and four of the five incorporate continuous geographic distance components rather than being calculated at the regional level.

One of the advantages of micro-level data in terms of modeling potential agglomeration economies lies in being able to include the spatial attenuation of agglomeration influences with increasing distance. The LRD provides establishment locations by county, allowing for substantial spatial variation at a scale smaller than most LMAs, an enormous improvement over regionally-invariant agglomeration measures (Wallsten 2001). Although an effective travel time metric based on road or other transportation networks would be better from a theoretical standpoint, data limitations restrict the analysis to calculated great circle distances, with county locations approximated by their geographic centroids.

[65] The correlation between the logarithms of population and population density is on the order of 0.6 to 0.8 for each industry-year sample.

As with regional industrial dominance, there is no strong theory that suggests a particular specification for modeling changes in the influence of agglomeration economies with distance (Hoogstra and van Dijk 2004). One specification in the literature is based on the expression for gravitational potential, with the decline in influence proportional to the percent change in distance (Anselin 2002; Hu and Pooler 2002). This supplies the reasonable property that small differences in distance are more important when the separation from the target location is small than when the separation is large. This type of distance decay is modeled with the reciprocal of an exponential term, applying a weight factor of $d^{-\alpha}$, where d is distance and α is a parameter that can be varied. The choice of $\alpha=1$ yields the inverse of distance. This functional form is standard for spatial applications ranging from migration to consumer marketing to knowledge spillovers and other agglomeration economies (e.g., Drezner and Drezner 1996; Fischer and Varga 2003; Tiefelsdorf 2003; Crozet *et al.* 2004; Lim 2004; van Soest *et al.* 2006). Figure 5.1 illustrates the decay profiles generated by varying the α parameter. Although it is possible to specify distance decay with any number of functional forms that yield varying shapes, this analysis uses only the reciprocal exponential specification for the sake of brevity and to help limit the complexity of the analysis. A cutoff distance is imposed beyond which interaction is presumed to be zero. Not only does the cutoff simplify the distance computations, but it also permits the pattern of decay to begin to approximate more complex functional forms without

Figure 5.1. Alternative Spatial Decay Profiles.



requiring additional computational parameters.[66] Alternative decay parameters were tested empirically, with the relatively rapid decay $\alpha = 1$ selected as the best fit for the densely concentrated measuring and controlling devices industry and the more gradual decay $\alpha = 0.1$ preferred for the less highly concentrated rubber and plastics and metalworking machinery industries.

Labor pooling, LP_{kx}, is measured as an establishment's access to workers with skills that roughly match the industry's expected occupational requirements:

$$LP_{kx} = \sum_c \left(\frac{O_{cx}}{O_{cT}} d_{ck}{}^{-\alpha} \right) \tag{5.14}$$

[66] For example, an inverse exponential decay with α=0.1 and a maximum distance of 100 miles roughly simulates a concave decay profile.

where x is the study industry, c indexes counties, k is the county of the target establishment, O_{cx} is county c's residential workforce employed in the top 15 occupations employed by industry x nationally, O_{cT} is county c's total residential workforce, and d_{ck} is the distance between county c and the county of the target establishment, measured between county centroids, for distances of 75 miles or less and zero otherwise.[67] The labor pooling measure is relative in that it is based on the fraction of each county's workforce in occupations of interest to the study industry rather than the total size of the available labor pool. Tests of substitute labor pooling variables utilizing absolute scales demonstrate serious multicolinearity issues with the other agglomeration indicators. The 15 occupations with the most employment in each study industry are identified from the *National Staffing Patterns* matrices of the United States Bureau of Labor Statistics (n.d.-b) (see Appendix 4). Values for O_{cx} and O_{cT} are obtained from the 1990 and 2000 Census *Equal Employment Opportunity* tabulations (United States Census Bureau 1993; 2004).[68]

Potential supply pools of manufactured inputs and producer services are calculated separately but similarly by weighting the local presence of supplier industries by the importance of each industry as a supplier to the study industry at the national level. Manufacturing input supply pooling, SP_{kx}, is:

$$SP_{kx} = \sum_{c}\left(\left(\sum_{m}\frac{E_{cm}P_{xm}}{P_{xM}}\right)\cdot d_{ck}{}^{-\alpha}\right) \tag{5.15}$$

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[67] The number of top occupations to include and the cutoff distance were determined empirically by testing alternatives. For the measuring and controlling devices industry, the rapidity of the distance decay means that the distance cutoff has little effect on the labor pooling variable. Alternative decays and cutoff distances are investigated in section 8.2.

[68] Census occupational data are based on worker residences rather than workplace locations. This is appropriate because home-to-work commuting preferences rather than distances between worksites determine available labor pools.

where m indexes manufacturing industries, x signifies the study industry, c indexes counties, k is the county of the target establishment, E_{cm} is county c's employment in industry m, P_{xm} is the dollar amount that the study industry purchases nationally from supplier industry m, P_{xM} is the study industry's total national purchases from manufacturing sector, and d_{ck} is again the distance between county c and the county of the target establishment, measured between county centroids, for distances of 75 miles or less and zero otherwise. Producer services pooling, SD_{kx}, is given nearly the same formula except that purchases and local employment are totaled for suppliers of producer services:

$$SD_{kx} = \sum_c \left(\left(\sum_s \frac{E_{cs} P_{xs}}{P_{xS}} \right) \cdot d_{ck}{}^{-\alpha} \right) \tag{5.16}$$

where s indexes producer services industries and P_{xS} is the study industry's total national purchases of producer services. The purchase amounts are constructed from the Make and Use tables of the *Benchmark Input-Output Accounts of the United States* from the Bureau of Economic Analysis (n.d.) (see Appendix 5). The E_{cm} and E_{cs} are tabulated from the *Longitudinal Business Database* (LBD).[69]

Knowledge spillovers are typically proxied by input measures such as university research expenditures and the density of employment of scientists and engineers, or outcome measures such as patents or new inventions (Jaffe *et al.* 1993; Fritsch and Lukas 1999; Fritsch and Meschede 2001; Kirchhoff *et al.* 2002b; Koo 2002). For this study, the relevant construct is access to potential sources of knowledge, rather than aggregate

[69] The *Longitudinal Business Database* and *County Business Patterns* are constructed from the same underlying confidential data.

outcomes. The measure of potential labor pooling already accounts for the concentration of scientists and engineers.

Two measures indicate different types of knowledge spillovers. The first, RS_{kx}, gauges regional access to relevant basic research and knowledge:

$$RS_{kx} = \sum_{c} \left(\left(\sum_{f} R_{cf} \right) \cdot d_{ck}^{-\alpha} \right) \tag{5.17}$$

where f indexes industry-relevant academic fields, R_{cf} is the total amount of research expenditures in academic field f during the previous five years at research universities located in county c, and the other variables are as in equations 5.14, 5.15, and 5.16. The maximum distance is 200 miles, since university-industry interactions in general need occur with less frequency and convenience than labor and supply interactions to have significant impacts upon firm practices (Matkin 1990; Tornatzky and Fleischer 1990). The fields relevant to each industry are identified from a Carnegie Mellon survey of industrial research and development managers analyzed in Cohen *et al*. (2002), along with the author's judgment.[70] Annual university research expenditures by academic field (in nominal dollars) are tabulated from the National Science Foundation's CASPAR database.

Second, patenting activity provides an indication of the extent of private sector research activity and regional innovative culture. Many studies acknowledge faults with patents as a proxy for innovative activity, yet empirical research does suggest that patents are related to the market value of knowledge, and in any case there are few viable

[70] For rubber and plastics, the fields are chemistry, materials science, and chemical engineering. For metalworking machinery, the fields are materials science, computer science, mechanical engineering, and electrical engineering. For measuring and controlling devices, the fields are materials science, computer science, mechanical engineering, electrical engineering, and physics. These correspond roughly to the fields indicated by 35 percent or more of industry respondents as being "moderately" or "very" important to their research and development activities as reported in Table 3 in Cohen *et al*. (2002).

alternatives (Jaffe 1989; Jaffe *et al.* 1993; Henderson *et al.* 1998; Acs *et al.* 2002a; Agrawal and Cockburn 2003; Sampat *et al.* 2003). The measure of patenting activity, PS_{rx}, weights the volume of patents granted in each technology classification by the relative importance of those technology categories to the target industry:

$$PS_{rx} = \sum_{g \in K} \left(\frac{PAT_{gr}}{POP_r} N_{gx} \right) \tag{5.18}$$

where g indexes patent technology classifications, r signifies the region, x represents the study industry, K is the set of patent technology classifications relevant to the study industry, PAT_{gr} is the number of utility patents granted within region r in the last five years in patent technology class g, POP_r is the regional residential population, and N_{gx} is a measure of relevance derived from tabulations of patent citations. Unlike the other four agglomeration variables, the patent measure incorporates geography solely in terms of regional boundaries.[71]

Cross-industry knowledge spillovers are taken into account in determining the set of relevant patent classifications by using the inter-industry technology flow matrix developed by Koo (2005a) to identify the particular industries that generate patents that are cited in at least five percent of the study industry's patents. K is then the set of patent technology classifications relevant to this group of cited industries. The relative importance of each cited industry is included by multiplying by N_{gx}, the citation frequency taken from the technology flow matrix (see Appendix 6). The patent counts are obtained from CASSIS (Classification and Search Support Information System) of

[71] Although it is theoretically possible to construct relatively sophisticated measures incorporating spatial decay as well as industry-specific attributes using publicly available patent data, problems of geographic assignation and temporal truncation of citations make such indicators extremely suspect for small spatial scales and restricted time periods (Hall *et al.* 2001).

the Information Products Division of the U.S. Patent and Trademark Office (1987-2002). The relevancy match is produced by the same agency (2004).

5.8. Controls

The production function equation includes several controls to account for additional characteristics that may impact productivity and agglomeration economies. At the establishment level, the dummy variable DE_z identifies establishments z that are part of firms classified as dominators according to the concentration ratio measure of regional industrial dominance. In other words, dominator establishments are those belonging to the five largest firms. Plants within firms reporting less than ten percent of the shipment value of the smallest regional industrial dominator firm are identified as small establishments with the dummy variable SE_z. The largest and smallest firms in a region may evidence different behavior with respect to productivity, regional industrial dominance, and agglomeration economies (see section 3.3).

Census Regions proxy macro-regional levels of development and economic conditions. Three dummies (*CR1*, *CR2*, and *CR3*) identify plants located in the South, Midwest, and West; the Northeast is the default region.[72] Regional unemployment rates (UE_r) and median household income levels (INC_r) signal local economic conditions (United States Bureau of Labor Statistics n.d.-a; United States Census Bureau n.d.-b). Population density (POP_r) helps control for regional size, level of resources, and the

[72] The Northeast region consists of Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont. The South region is Alabama, Arkansas, Delaware, the District of Columbia, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, and West Virginia. The Midwest region contains Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. The West region is Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming.

absolute dimension of potential agglomeration economies, as well as urban congestion and other agglomeration diseconomies (United States Census Bureau n.d.-c). The unemployment, income, and population density variables are constructed for LMAs by combining county-level estimates.

Regional industrial diversity, like dominance, is an aspect of industrial structure theorized to influence establishment-level productivity. Specifically, Jacobs-type externalities benefit regions with diverse economies that generate knowledge spillovers across industries and types of economic activity (see sections 2.4.1 and 2.4.2.3). Large urban agglomerations are likely to be those that are industrially diverse, but detailed industry data can be used to distinguish diversity from size-based urbanization advantages (Duranton and Puga 2000). As is common in the agglomeration literature, a Herfindahl-Hirschman index calculated across regional industries at the four-digit SIC level of aggregation, DV_r, serves to measure regional industrial diversity:

(5.19) $$DV_r = \sum_x \left(\frac{E_{rx}}{\sum_x E_{rx}} \right)^2$$

where r indicates the region, x indexes industries, and E is employment. The data are drawn from the *Longitudinal Business Database* in order to incorporate all industrial sectors in the diversity measure rather than just manufacturing; employment takes the place of shipment value because the LBD does not provide plant-level output information. As constructed, DV_r actually measures the inverse of diversity—greater values of the Herfindahl-Hirschman index in equation 5.19 indicate lesser regional industrial diversity.

Because the effects of regional industrial dominance or industrial diversity on establishment performance may be cumulative or otherwise persist over time, an historic version of each measure is included to help distinguish long-term effects. To avoid multicolinearity, historic dominance (DH_{rx}) and historic diversity (DVH_r) are expressed as the change in dominance and diversity, respectively, over the twenty year period leading up to the year of the sample, with the calculation procedure for the historic measure matching that of the sample year version. Also because of multicolinearity issues, the productivity estimations contain only one historic measurement for each of dominance and diversity, and these two industrial structure variables are the only factors for which historic versions are incorporated. The particular period of twenty years is a functional compromise: representing sufficient time for substantial change to occur yet short enough to retain the functional coherence of the industry and regional definitions and remain within the period of available data. Because the LBD is not available for 1972, the change in diversity is measured over a fifteen-year period for the 1992 samples.

An additional control variable, the percentage of resident adults (age 25 and older) possessing at least a bachelor's degree (ED_r), was originally intended to signify in broad terms the depth of the regional human capital base, with educational attainment information at the county level taken from the decennial national censuses (United States Census Bureau 1990; 2000). Income and education proved to be highly positively correlated, however, leading to substantial multicolinearity in the production function regressions. Preliminary model testing demonstrated that the income variable possesses greater interregional variation and yields superior performance in the regression analyses, so the education control is omitted from the production function equation.

5.9. Full Model Equations

All of the variables except dummies are mean centered to enter the production function. This procedure eases the interpretation of model outputs by causing the estimated parameters to refer to the direct effects at the sample means of the other variables rather than at their zero points. The coefficients and standard error estimates in the translog system are not substantively altered.[73] In addition, those variables that are not already measured in percentage or ratio form are transformed with natural logarithms. The resulting coefficient estimates for the transformed variables can be interpreted directly as elasticities at the sample means.

Table 5.3 lists the full set of production function variables.

[73] The estimates produced are identical once adjusted for the alteration of the mean points. Unfortunately, mean centering does not reduce variable multicolinearity, despite some claims to the contrary (Aiken and West 1991; Gatignon and Vosgerau 2005; Brambor and Clark 2006).

Table 5.3. Production Function Variables.

Category	Variable		Description	Unit
dependent	Q	output	value of shipments	establishment
standard inputs	K	capital	gross book assets plus capitalized rentals	establishment
	L	labor	production-worker-equivalent hours	establishment
	E	energy	quantity of electricity and fuels	establishment
	M	materials	value of purchased materials and services	establishment
dominance	D	*one of four alternatives:*		industry-region
		D_C (concentration ratio)	percent of shipments in five largest firms	
		D_H (Herfindahl-Hirschman)	sum of squared firm shipment shares	
		D_R (Rosenbluth)	sum of firm shipment shares weighted by descending size rank	
		D_G (Gini)	degree of inequality in firm shipment shares	
agglomeration economies	LP	labor pooling	percent of local employment in top industry occupations	industry-county
	SP	manufactured input pooling	percent of local employment in top manuf. supply industries	industry-county
	SD	producer services pooling	percent of local employment in producer services	industry-county
	RS	research	university research expenditures in industry-relevant fields	industry-county
	PS	patents	industry-relevant patent rate per capita	industry-region
controls	DE	dominator	establishment belongs to one of top five firms (dummy)	establishment
	SE	small	shipments < 10 percent of smallest dominator firm (dummy)	establishment
	CR1	geographic region	South (dummy)	region
	CR2		Midwest (dummy)	region
	CR3		West (dummy)	region
	POP	population	population density	region
	UE	unemployment	unemployment rate	region
	INC	income	median household income	region
	ED	education	percent 25 or older with bachelor's degree or higher	region
	DV	industrial diversity	Herfindahl-Hirschman index with industry employment shares	region
	DH	historic dominance	dominance 20 years earlier (construction matches dominance)	industry-region
	DVH	historic diversity	industrial diversity 20 years earlier	region

Note: ED (educational attainment) dropped from final models due to multicolinearity.

Using the notation of section 4.5 and suppressing the analysis unit indices, the full translog production function equation including all interaction terms is:

(5.20)
$$
\begin{aligned}
\ln Q = {} & \alpha_0 + \alpha_k \ln K + \alpha_l \ln L + \alpha_e \ln E + \alpha_m \ln M \\
& + \frac{1}{2}\beta_{kk}(\ln K)^2 + \frac{1}{2}\beta_{ll}(\ln L)^2 + \frac{1}{2}\beta_{ee}(\ln E)^2 + \frac{1}{2}\beta_{mm}(\ln M)^2 \\
& + \beta_{kl} \ln K \ln L + \beta_{ke} \ln K \ln E + \beta_{km} \ln K \ln M \\
& + \beta_{le} \ln L \ln E + \beta_{lm} \ln L \ln M + \beta_{em} \ln E \ln M \\
& + \gamma_d D + \gamma_{lp} LP + \gamma_{sp} \ln SP + \gamma_{sd} \ln SD + \gamma_{rs} \ln RS + \gamma_{ps} \ln PS \\
& + \frac{1}{2}\delta_{dd}\left(D^2\right) + \delta_{dlp}\left(D \cdot LP\right) + \delta_{dsp} D \ln SP \\
& + \delta_{dsd} D \ln SD + \delta_{drs} D \ln RS + \delta_{dps} D \ln PS \\
& + \lambda_{dk} D \ln K + \lambda_{dl} D \ln L + \lambda_{de} D \ln E + \lambda_{dm} D \ln M \\
& + \lambda_{lpk} LP \ln K + \lambda_{lpl} LP \ln L + \lambda_{lpe} LP \ln E + \lambda_{lpm} LP \ln M \\
& + \lambda_{spk} \ln SP \ln K + \lambda_{spl} \ln SP \ln L + \lambda_{spe} \ln SP \ln E + \lambda_{spm} \ln SP \ln M \\
& + \lambda_{sdk} \ln SD \ln K + \lambda_{sdl} \ln SD \ln L + \lambda_{sde} \ln SD \ln E + \lambda_{sdm} \ln SD \ln M \\
& + \lambda_{rsk} \ln RS \ln K + \lambda_{rsl} \ln RS \ln L + \lambda_{rse} \ln RS \ln E + \lambda_{rsm} \ln RS \ln M \\
& + \lambda_{psk} \ln PS \ln K + \lambda_{psl} \ln PS \ln L + \lambda_{pse} \ln PS \ln E + \lambda_{psm} \ln PS \ln M \\
& + \nu_{de} DE + \nu_{se} SE + \nu_{cr1} CR1 + \nu_{cr2} CR2 + \nu_{cr3} CR3 \\
& + \nu_{pop} \ln POP + \nu_{ue} UE + \nu_{inc} \ln INC + \nu_{dv} DV \\
& + \rho_{dh} DH + \rho_{dvh} DVH + \varepsilon
\end{aligned}
$$

and the cost share equations are, for $i = K$, L, E, and M:

(5.21)

$$
S_i = \frac{\alpha_i + \sum_j \beta_{ij} \ln X_j + \lambda_{di} D + \lambda_{lpi} LP + \lambda_{spi} \ln SP + \lambda_{sdi} \ln SD + \lambda_{rsi} \ln RS + \lambda_{psi} \ln PS}{\sum_j \alpha_j + \sum_i \sum_j \beta_{ij} \ln X_j + \sum_i \left(\lambda_{di} D + \lambda_{lpi} LP + \lambda_{spi} \ln SP + \lambda_{sdi} \ln SD + \lambda_{rsi} \ln RS + \lambda_{psi} \ln PS\right)}.
$$

5.10. Additional Validity Concerns

Beyond the discussion of potential endogeneity in section 4.7, there are further validity concerns that arise from the particular selection of variables and methods of construction. The most serious problem is the lack of a measure assessing the availability of capital, since constraints on external financing is one of the three postulated mechanisms by which regional industrial dominance is hypothesized to affect productivity via agglomeration economies.[74] To the extent that the influence of regional industrial dominance on sources of financing follows the patterns of the other measured agglomeration economies, the estimated agglomeration parameter coefficients may include the effects of capital availability.

Some researchers investigating agglomeration economies include indicators of customer demand proximity or pooling (e.g., Feser 2002; Renski and Feser 2004; Renski 2006). There are two chief reasons why demand pooling is not included in this analysis. First, the production of each of the three study industries is concentrated on a variety of intermediate outputs that are then used as inputs in a broad range of subsequent manufacturing. Demand pooling is likely not as important for these industries as it might be for an industry with a relatively limited set of products and purchasers. Second, severe multicolinearity issues arise when a measure of intermediate demand is introduced, since many of the establishments that purchase the primary outputs of the three study industries are either within the study industry classifications themselves or have quite similar labor requirements. Still, to the degree that demand pooling (or another unexplored agglomeration economy) is present and not accounted for by the

[74] One of the key justifications for conducting case studies as part of the larger research project is to enable the exploration of credit availability and capital financing in general (see footnote 11 in Chapter 2).

included agglomeration measures, there may be an unexplained influence on the regression results.

The independent variables described in this chapter contain measurement flaws. For example, the shortcomings of patents as a measure of knowledge spillovers are well documented (e.g., Jaffe *et al.* 1993; Sampat *et al.* 2003). Geographic locations are assigned to patents by county according to the first listed inventor. The crosswalk between patent technology classifications and industries is approximate at best and, because it refers to relationships at the national scale, does not capture local variations in innovation propensities and utilization of knowledge resources. Occupation is an imperfect proxy for worker skills, and Census occupational data likely undercount available labor pools because they do not include workers that are unemployed, underemployed, or inactive in the labor force. The capital input measure does not reflect depreciation over time, and both the capital and labor variables presume full capacity utilization. The standard industrial classification systems (SIC and NAICS) sort establishments into industries on the basis of similarities in primary production technologies, largely ignoring factors such as similarity in demand markets (i.e., substitutability among products manufactured with different production techniques), the sales of secondary products, and the distinction between producer and consumer services (Hay and Morris 1991; Wernerheim and Sharpe 2001). The measures of regional industrial dominance, potential agglomeration economies, and regional controls such as industrial diversity are unavoidably predicated upon the industry classification systems and incorporate their limitations. It is likely that the other independent variables possess faults as well. Nevertheless, the construction of each independent variable is the best that can be accomplished with the data that are available on a national basis and follows techniques employed successfully in earlier research. As with all empirical research, as long as the irregularities do not introduce systematic bias, the consequence of imperfect variables is a reduction in the clarity and statistical strength of the estimation results. This study counters measurement error to some degree with substantial sample size and plant-level detail.

The production output variable for this study is assembled in typical fashion from the data items available in the LRD. Several concerns related to its construction, however, are worth specific consideration. Although the issues may or may not be mentioned in publications (usually they are not), they apply to most micro-level empirical analyses of productivity. First, Ciccone and Hall (1996) argue that the production value data in the CM are inappropriate for studying productivity and agglomeration economies, since they reflect the use of services purchased in the market or transferred from other establishments within the same corporation that go unmeasured in the dataset. Essentially, increases in service outsourcing that raise production amounts could be erroneously perceived as increases in productivity, and, since outsourcing is likely to be disproportionately larger in dense urban locations, might be mistaken for urbanization economies. As Henderson (2003) notes, the CM did not record plant services purchases prior to 1992. This analysis, however, incorporates within the material input variable several measures of service purchases that are available in the recent CM years. While not necessarily complete, these components track a good portion of plant-level service purchases. Moreover, because this analysis studies direct indicators of potential agglomeration economies rather than letting indirect measures such as urban size or population density serve as proxies, it is much less likely that outsourcing availability will be confused with agglomeration advantages in relationship to productivity. Ciccone and Hall's comment does illustrate an additional reason for caution in conducting empirical productivity analyses: even the best data available at the plant level may incorporate idiosyncrasies into the measurement of production inputs and output that interfere with estimating the influences of interest.

Another potential problem arises from using the value of shipments as the measure of output for productivity analysis. Production value data may be influenced by differential prices resulting from imperfect competition. To the extent that plants in the same industry offer differentiated products, or engage in price competition, for example by using cost advantages to undercut competitors' prices and expand market share rather than accumulate profit, sales value may not reflect equally the production of real output across establishments. Klette and Griliches (1996) suggest addressing this concern by including a measure of real output in addition to the value of production, a solution that is not possible in the context of the LRD. Instead, this study follows the lead of most other empirical analyses by relying on its initial assumptions—the homogeneity of products and production technology within industries, and profit-maximizing behavior—in measuring output with shipment value. These assumptions make sense for the particular study industries, are more reasonable at the establishment level and within individual regions than at the national scale, and are more likely to hold for smaller firms that possess little market power. Furthermore, whereas Klette and Griliches argue that price competition can yield a systematic downward bias in production as measured by sales value, variations in product quality and departures from immediate profit-maximizing behavior in the direction of higher prices may occur as well.

Finally, McCombie (2000; 2001) asserts that the estimation of a production function that involves an output variable defined in value rather than quantity terms, whether conducted at an aggregate or the individual establishment level, is invalid. His argument is logical rather than empirical: the value measurement of output relies on the accounting identity relating inputs and input prices with output in order to calculate the value added by the production process. The accounting identity is:

$$Q \equiv wL + rK \tag{5.22}$$

where Q is output, L and K are labor and capital stocks, w is the wage rate, and r is the rate of profit.[75] Production function estimation thus reproduces the underlying accounting identity statistically, rather than approximating an independent production function. McCombie declares that there is no way to independently test the form or even the existence of a production function because of this fundamental and confounding identity.

The background of McCombie's argument lies in the so-called Cambridge Capital Theory Controversies of the 1950s through the 1970s, in which the "Cambridge" group of economists (mainly associated with either Cambridge, England, or Cambridge, Massachusetts, and opposed by a counterpart assembly of academicians dubbed the "American" side) argued among other things that capital inputs cannot usefully be measured in an aggregate combination of different sorts of capital (Cohen and Harcourt 2003). The Cambridge economists also contended that aggregate production functions

[75] Equation 5.22 reproduces equation 6 in McCombie (2000).

combining different inputs and outputs are not theoretically meaningful. These debates were never resolved, but rather faded from the spotlight as the scholars prominent in the controversies retired from active research and publication. The body of production function research largely accepts the premise of multiform capital inputs and aggregate production functions without reference to a solid refutation of the Cambridge criticisms.

Ultimately, the response to McCombie's criticism of production function research is similar to that of the Capital Controversies: the literature generally accepts the existence of well-behaved production functions even lacking a legitimate formal test, and disregards the question of whether statistical estimations measure production functions or an accounting identity that presents the same functional form. The specific characteristics of this analysis provide additional responses. The CM questionnaire instructs establishments to report shipment value from actual sales receipts, whereas the information regarding input prices used in the production function estimation is collected from secondary sources at aggregated levels. Therefore, the data that enter the production function are not produced according to the accounting identity. Lastly, the production function specified in equations 4.9 and 5.20 involves additional factors into production other than the standard inputs, including regional industrial dominance and possible sources of agglomeration economies along with other regional characteristics, so that the form of the estimating production function is distinct from the simple accounting identity.

5.11. Summary

This chapter detailed the data sources, regions, selection of study industries, and creation of the variables that populate the estimation model. The variable construction is guided by both theoretical and empirical criteria but is constrained by the available data and statistical issues. The versions described in this chapter represent the outcome of substantial consideration and testing of alternatives, undertaken with the goal of adopting the most construct valid measures possible that avoid excessively high multicolinearity. Four different indicators of regional industrial dominance are included and their results contrasted in the succeeding chapters in order to investigate a concept not before explicitly operationalized. Potential agglomeration economies are measured utilizing a wide variety of secondary data sources and, except for patenting propensity, incorporate distance attenuation as measured between county centroids. The next chapter examines summary statistics for the estimation samples and variables.

CHAPTER SIX: DESCRIPTIVE INFORMATION

6.1. Introduction

Chapter Five described the construction of the industry samples and variables; this chapter considers descriptive information concerning their characteristics. It is important to note that the study samples constitute censuses rather than random samples of American manufacturing establishments; standard statistical inferences are not as meaningful in this context. The estimation samples are not complete censuses since some categories of observations are omitted. Section 6.2 considers the relationship between the estimation samples and the industries on the national scale. The remainder of the chapter focuses on descriptive statistics pertaining to the independent and dependent variables. Pearson pairwise correlation coefficients are calculated for the nine industry-year samples to investigate possible multicolinearity issues and the degree to which the model variables represent distinct concepts.

6.2. Estimation Samples

The nine industry-year sets of establishments are not random samples drawn from a larger population. The samples initially drawn from the LRD each constitute a full census of the particular manufacturing industry in the United States.[76] The final samples

[76] More precisely, the portion of the manufacturing industry that is located outside of six excluded LMAs: the three LMAs covering central New York, Los Angeles, and Chicago, and the other three LMAs that comprise the states of Alaska and Hawaii.

used in the regression analyses include all establishments classified in the industry that year that report positive employment and meet the criteria required to support production estimations and the measurement of regional industrial dominance. Therefore, the study samples are better characterized as a census than as a representative sample. The implication is that less emphasis should be placed on interpreting inferential statistics with regard to a hypothetical encompassing population. Regression analyses typically highlight the statistical significance of coefficient estimates to indicate whether repeated samples drawn from the sampling frame would on average demonstrate effects different from zero. In the context of a census, however, there are no repeated samples. Consequently, though standard errors and statistical significance are still examined in this study to gauge the strength of the estimation results, more attention is given to interpreting the signs and magnitudes of the estimated parameters.

The observations excluded from the full population of study industry establishments originally drawn from the LRD fall into three categories: administrative records for which most data items are imputed; observations with non-positive input, output, or cost share measures; and plants located in regions with an insufficient number of firms in the study industry to consider meaningfully the concept of regional industrial dominance. Administrative records constitute by far the largest of these three categories. In removing those establishments exempted from standard reporting requirements, primarily plants with five or fewer employees, the samples exclude the very smallest producers. Once administrative records are dropped from the samples, only a few observations contain invalid output or standard input quantities or cost shares. A substantial number of establishments are located in regions with fewer than twelve firms in the study industries, particularly in the measuring and controlling devices industry (SIC 382), and are omitted from the analysis samples.

Table 6.1 describes the sets of establishments contained in the nine industry-year samples. There are several thousand plants in the rubber and plastics (SIC 30) and metalworking machinery (SIC 354) samples in each of the three study years. The measuring and controlling devices (SIC 382) samples are smaller but still possess more than 1,200 observations each. These sample sizes are large in the context of a productivity estimation study. In each industry, the number of plants rises from 1992 to 1997 but then falls substantially in 2002, likely due to the continuing decline in manufacturing combining with the economic downturn of the early part of the new century. It is also possible that the change to NAICS industry definitions affects the total number of plants classified within the study industries for the 2002 samples.
Somewhat more than half of all the original LRD observations are contained in the final samples for the rubber and plastics and the metalworking machinery industries, and slightly more than a third in the measuring and controlling devices industry. The lower retention rate of measuring and controlling devices plants results mainly from a higher proportion of administrative records in that industry. The measuring and controlling devices industry also has a more concentrated geographic distribution, so that many of the plants not sited within a major agglomeration are instead located in regions with fewer than twelve firms in the industry. The mean plant sizes, whether measured by employment or shipment value, are not very large: less than 100 employees in rubber and plastics and measuring and controlling devices, and fewer than 40 employees in the metalworking machinery industry. Establishment sizes have increased over the time

Table 6.1. Characteristics of Study Samples.

SIC	30			354			382		
Industry	rubber & plastics			metalworking machinery			measuring & controlling devices		
Year	1992	1997	2002	1992	1997	2002	1992	1997	2002
Sample observations	6,747	8,000	6,546	5,189	5,490	4,161	1,384	1,540	1,201
Dropped observations	6,169	6,499	5,128	4,053	4,522	3,982	2,385	2,582	2,211
Percent retained in sample	52.2	55.2	56.1	56.1	54.8	51.1	36.7	37.4	35.2
Mean employment	78	82	91	33	38	36	97	94	111
Mean shipments	9,912	12,789	16,259	3,417	5,191	5,185	12,891	17,603	22,393
Dominator establishments	645	833	901	427	497	505	167	212	202
Percent	9.6	10.4	13.8	8.2	9.1	12.1	12.1	13.8	16.8
Mean employment	286	280	273	148	154	123	410	359	409
Mean shipments	46,714	56,044	60,529	19,014	27,802	22,238	61,399	80,882	92,503
Dominated establishments	3,061	3,701	2,487	2,686	2,886	1,846	658	687	505
Percent	45.4	46.3	38.0	51.8	52.6	44.4	47.5	44.6	42.0
Mean employment	23	24	26	13	15	15	21	23	23
Mean shipments	1,835	2,254	2,835	964	1,462	1,562	1,958	2,800	3,056
Remainder of establishments	3,041	3,466	3,158	2,076	2,107	1,810	559	641	494
Percent	45.1	43.3	48.2	40.0	38.4	43.5	40.4	41.6	41.1
Mean employment	89	97	91	36	41	34	93	82	80
Mean shipments	10,236	13,642	14,199	3,384	4,966	4,122	11,269	12,540	13,491

Note: Value of shipments reported in thousands of nominal dollars.

frame of the samples, reflecting the trend of contraction and consolidation throughout the manufacturing sector. The plants retained in the final samples are larger in terms of average employment or shipment value than those dropped, an additional reminder that the analysis does not include the very smallest manufacturers.

The fraction of sample observations that are classified as dominators, as defined with regard to the five-firm concentration ratio measure detailed in section 5.6, ranges from approximately one in twelve in the 1992 metalworking machinery sample to about one in six in measuring and controlling devices in 2002. A greater percentage of establishments are part of relatively large firms in the later samples, again due to consolidation into relatively large companies accompanying declining total manufacturing employment. The measuring and controlling devices industry sample has a somewhat larger percentage of dominators than the other two study industries. Of the non-dominator plants, roughly half are relatively small, belonging to firms with less than ten percent of the shipment value of the smallest dominator firm in their region, and the remainder do not belong to either dominator or dominated firms.

As should be the case given the classification criteria, dominator plants are relatively large. Rubber and plastics establishments that are part of regional dominator firms average more than three times the employment and about four times the shipment value of the typical plant across the entire sample. The mean size of the dominator plants is ten to twenty times greater than dominated plants across all regions, demonstrating the right-skewed nature of the establishment size distribution. The comparisons hold similarly for the other two study industries, with dominators averaging as much as twenty to thirty times larger than plants in small firms in the measuring and controlling devices industry.

All three of the study industries evidence substantial spatial concentration. The sample plants are mostly located in relatively dense, urban counties, those that are within the boundaries of Metropolitan Statistical Areas (MSAs). The exclusion of plants in regions with fewer than twelve industry firms accounts for a portion of this urban tilt. Yet even in the full LRD dataset, establishments in all three industries are sited in metropolitan counties well more often than not, following patterns of population and sources of production inputs. The measuring and controlling devices industry has the most restricted geographic scope: only about ten percent of the non-excluded LMAs are represented in the final samples, and a substantial fraction of the sample observations are situated in a few counties located on the east and west coasts. A plurality of the establishments in the measuring and controlling devices samples are in the Northeast

Census Region. The other two industries contain establishments spread across more than 100 regions (LMAs), though the Midwest Census Region accounts for close to half of the rubber and plastics establishments and a majority of the plants in the metalworking machinery samples. Dominator establishments are less likely than the average plant to be located in populous counties, since the definition of regional industrial dominance is based on relative size and thus generates a higher threshold in regions with more or larger firms. Conversely, dominated establishments are more frequently sited in heavily inhabited counties.

The fact that the estimation samples are chiefly urban and leave out regions with few establishments leads to problems in modeling potential agglomeration economies. The fewer regions spanned by the samples, the less variation in regional measures and correspondingly the greater tendency toward multicolinearity among the agglomeration variables and other regional indicators. The issue of multicolinearity is discussed further in section 6.4. The urban nature of the samples also means that the results of the analysis do not extend generally to establishments located across the entire range of the urban-rural hierarchy.

6.3. Variable Characteristics

Descriptive statistics for the standard input and output variables are displayed in Table 6.2. Due to restrictions imposed to protect the confidentiality of individual responses, it is not possible to present medians or other percentile statistics. Instead, Table 6.2 (as well as Tables 6.3 and 6.4) reports the percentage of observations placing above the sample mean for each variable as an indicator of the degree of asymmetry in the sample. Across all three study industries, the small fraction of plants with output and standard input quantities greater than the mean again demonstrates the right-skewed nature of the samples in terms of size: there are many more establishments below the average than above, and there is greater dispersion (i.e., a longer tail) on the large side of the size continuum.

The largest portion of production costs in the rubber and plastics industry is due to expenditures for materials. Labor costs predominate in the metalworking machinery industry, and the measuring and controlling devices industry spends roughly equally on labor and materials, with those two factors constituting the majority of production costs. Energy is a only a small fraction of total production expenditures. The share of capital costs rises over the ten years represented in the three samples for each study industry, as perhaps another reflection of the consolidation process in manufacturing that results in greater concentration in larger and more heavily capital-invested plants. The metalworking machinery industry is more labor-intensive in production than are the other two study industries, as evidenced by the high labor cost share and the low output per production hour in the samples, yet also has the highest capital-to-labor ratio of the three industries. The capital-to-labor ratio is much lower in the measuring and controlling devices manufacturing plants, an industry engaging in relatively technology-intensive manufacturing. Based on these indications, labor pooling advantages might be most important to measuring and controlling devices establishments and least important in the rubber and plastics industry. In addition, knowledge spillovers would presumably be the most influential for productivity in higher technology economic activities, in this study represented by the measuring and controlling devices samples.

Table 6.2. Input and Output Variables: Descriptive Information.

SIC 30: Rubber and Plastics										
Year / Sample observations		1992 (n = 6,747)			1997 (n = 8,000)			2002 (n = 6,546)		
		mean	std dev	%>mean	mean	std dev	%>mean	mean	std dev	%>mean
Output	Q	9,931	23,685	25.17	12,814	28,614	25.36	16,272	33,279	25.31
Capital	K	4,856	16,606	21.73	6,286	19,748	22.16	9,166	24,751	22.53
Labor	L	193	322	27.66	201	339	27.91	218	362	28.23
Energy	E	18,997	54,866	22.62	22,199	64,385	21.93	28,054	81,757	21.77
Materials	M	4,749	11,810	24.14	6,142	14,379	24.15	7,542	16,334	24.17
Capital Cost Share	C_K	13.82	8.01	39.91	17.81	9.28	48.56	21.13	10.23	46.62
Labor Cost Share	C_L	35.56	13.81	44.40	32.77	13.29	42.85	31.67	12.80	43.23
Energy Cost Share	C_E	2.89	2.32	38.34	2.39	1.92	34.91	2.35	1.93	36.80
Materials Cost Share	C_M	47.74	16.10	53.18	47.03	15.66	54.61	44.85	15.28	53.07
Capital-Labor Ratio	K/L	21.70	22.64	31.29	28.70	32.45	31.50	38.97	43.12	32.36
Output per Worker Hour	QHR	50.22	49.13	32.61	65.04	59.13	32.06	76.02	71.10	31.64

SIC 354: Metalworking Machinery										
Year / Sample observations		1992 (n = 5,189)			1997 (n = 5,490)			2002 (n = 4,161)		
		mean	std dev	%>mean	mean	std dev	%>mean	mean	std dev	%>mean
Output	Q	3,424	11,539	19.31	5,242	19,903	19.00	5,178	18,096	20.04
Capital	K	1,922	5,236	21.56	2,597	7,039	21.44	3,526	8,676	23.34
Labor	L	81	185	23.38	92	227	23.72	83	171	25.19
Energy	E	3,528	13,700	18.87	4,211	16,225	20.56	4,174	13,135	20.60
Materials	M	1,220	5,561	15.94	2,086	12,031	15.50	2,015	10,540	16.32
Capital Cost Share	C_K	8.78	5.03	37.75	12.90	7.00	45.12	14.25	7.46	38.84
Labor Cost Share	C_L	57.86	13.13	50.34	54.40	13.06	57.12	53.18	13.67	53.86
Energy Cost Share	C_E	1.65	1.29	38.12	1.43	1.37	34.94	1.36	1.35	33.60
Materials Cost Share	C_M	31.72	13.92	48.43	31.27	14.52	40.09	31.21	14.96	42.13
Capital-Labor Ratio	K/L	24.86	18.59	36.13	30.31	50.84	31.60	44.25	45.21	34.56
Output per Worker Hour	QHR	36.63	22.19	36.38	48.82	32.42	32.06	55.37	34.13	31.92

SIC 382: Measuring and Controlling Devices										
Year / Sample observations		1992 (n = 1,384)			1997 (n = 1,540)			2002 (n = 1,201)		
		mean	std dev	%>mean	mean	std dev	%>mean	mean	std dev	%>mean
Output	Q	12,852	38,353	20.23	17,611	63,498	17.73	22,181	77,746	18.15
Capital	K	4,744	15,682	18.50	5,854	25,133	17.47	8,880	33,063	16.82
Labor	L	274	673	22.47	261	667	21.88	320	878	20.57
Energy	E	7,787	24,120	17.05	8,065	29,751	17.27	9,039	33,750	16.74
Materials	M	4,833	15,570	19.51	6,571	25,789	17.73	9,394	42,542	16.40
Capital Cost Share	C_K	10.27	6.43	33.38	13.46	7.43	47.08	14.12	7.92	44.88
Labor Cost Share	C_L	47.41	12.24	47.90	43.98	11.62	42.99	44.19	12.64	44.05
Energy Cost Share	C_E	1.16	1.06	40.53	1.02	1.28	32.60	0.83	0.80	30.97
Materials Cost Share	C_M	41.16	13.49	53.47	41.54	13.74	56.04	40.86	14.65	56.37
Capital-Labor Ratio	K/L	14.66	15.50	33.02	19.25	16.45	38.12	24.94	23.91	34.47
Output per Worker Hour	QHR	44.46	27.64	38.01	60.83	56.26	32.21	67.08	54.40	31.06

Note: Output, capital, and materials in thousands of nominal dollars; labor in thousands of hours; energy in millions of BTUs.

The regional industrial dominance variables are detailed in Table 6.3. It is worth emphasizing that the dominance variable means do not represent directly the average level of dominance across the LMA regions in the study. Rather, they are sample means, and may be thought of as a weighted average of regional dominance in each study industry, where each region's measure of dominance is weighted by the number of firms in that regional industry. Perhaps the most striking characteristic is that the mean levels of absolute dominance reported in each industry sample rise consistently over the three study years. On average, a rubber and plastics establishment in the sample in 1992 is located in a region with 39 percent of the total shipment value of the regional industry concentrated in the five largest producers. This ratio rises to 45 percent in 2002 for rubber and plastics, is slightly higher in the metalworking machinery, and climbs as high as 64 percent in the measuring and controlling devices industry. The Herfindahl-Hirschman and Rosenbluth index measures of dominance, though lacking a straightforward numerical interpretation, follow the same pattern, indicating greater intra-industry regional dominance over time. Again, contraction and consolidation in the manufacturing sector likely explains the trend. The pattern agrees with observations of manufacturing industries at the national level (Pryor 2001). For the most part, the Herfindahl-Hirschman and Rosenbluth indices yield the same ordering of dominance across the study industries as the concentration ratio measure, with one exception being that the Rosenbluth index, which emphasizes smaller establishments, indicates greater dominance in rubber and plastics than in metalworking machinery manufacturing.

The Gini coefficient, which is the regional industrial dominance measure included in the study that does not depend on the size of regional industries, evidences much

Table 6.3. Dominance and Agglomeration Economy Variables: Descriptive Information.

SIC 30: Rubber and Plastics										
Year / Sample observations		1992 (n = 6,747)			1997 (n = 8,000)			2002 (n = 6,546)		
		mean	std dev	%>mean	mean	std dev	%>mean	mean	std dev	%>mean
Dominance										
Concentratio Ratio	D_C	0.3873	0.1910	47.81	0.4043	0.1945	47.11	0.4493	0.1983	42.27
Herfindahl-Hirschman	D_H	0.0656	0.0727	34.65	0.0711	0.0759	32.01	0.0787	0.0751	34.68
Rosenbluth	D_R	0.0411	0.0426	33.29	0.0454	0.0452	33.75	0.0577	0.0566	32.36
Gini	D_G	0.7203	0.0494	44.12	0.7278	0.0506	50.45	0.7118	0.0550	52.81
Labor Pooling	LP	0.0781	0.0129	39.32	0.0974	0.0249	42.76	0.1171	0.0279	44.70
Manufactured Inputs	SP	2,913	2,071	42.00	1,807	1,356	40.68	1,635	1,212	40.90
Producer Services	SD	25,567	28,550	27.95	12,517	13,345	30.88	13,878	15,073	30.58
Research	RS	330,729	242,436	38.94	406,037	274,997	41.69	501,543	322,954	41.87
Patenting	PS	21.22	9.61	48.39	21.09	10.71	47.14	23.62	12.42	45.75

SIC 354: Metalworking Machinery										
Year / Sample observations		1992 (n = 5,189)			1997 (n = 5,490)			2002 (n = 4,161)		
		mean	std dev	%>mean	mean	std dev	%>mean	mean	std dev	%>mean
Dominance										
Concentratio Ratio	D_C	0.4135	0.1960	46.98	0.4363	0.2088	48.43	0.4531	0.2011	42.20
Herfindahl-Hirschman	D_H	0.0790	0.0824	33.22	0.0894	0.0954	34.41	0.0898	0.1010	33.62
Rosenbluth	D_R	0.0386	0.0481	31.88	0.0442	0.0563	31.68	0.0536	0.0716	32.06
Gini	D_G	0.7250	0.0723	58.33	0.7482	0.0708	58.21	0.7302	0.0727	58.71
Labor Pooling	LP	0.1170	0.0109	47.95	0.1457	0.0145	55.01	0.1221	0.0204	56.28
Manufactured Inputs	SP	3,297	1,883	48.20	3,025	1,650	47.74	2,797	1,609	45.61
Producer Services	SD	22,113	22,927	31.18	9,866	9,857	30.46	10,660	11,130	30.09
Research	RS	497,467	377,447	38.95	725,256	475,313	39.69	924,617	555,602	44.20
Patenting	PS	18.37	6.78	48.24	18.52	8.31	46.28	21.02	10.07	48.88

SIC 382: Measuring and Controlling Devices										
Year / Sample observations		1992 (n = 1,384)			1997 (n = 1,540)			2002 (n = 1,201)		
		mean	std dev	%>mean	mean	std dev	%>mean	mean	std dev	%>mean
Dominance										
Concentratio Ratio	D_C	0.5425	0.1837	44.51	0.5915	0.1518	45.52	0.6433	0.1395	38.38
Herfindahl-Hirschman	D_H	0.1376	0.1493	34.25	0.1453	0.1208	26.10	0.1686	0.1232	30.06
Rosenbluth	D_R	0.0712	0.0670	37.28	0.0714	0.0589	35.84	0.0889	0.0636	33.97
Gini	D_G	0.8036	0.0516	41.04	0.8061	0.0566	57.34	0.8101	0.0695	62.86
Labor Pooling	LP	0.1369	0.0201	39.45	0.1958	0.0265	42.53	0.1514	0.0259	40.88
Manufactured Inputs	SP	1,728	2,167	25.22	2,374	4,113	18.31	2,051	3,194	22.90
Producer Services	SD	7,089	4,425	50.51	4,401	3,039	47.79	5,268	3,809	46.54
Research	RS	160,186	229,831	22.90	185,002	267,781	29.48	201,325	261,265	27.81
Patenting	PS	61.57	24.77	40.25	72.12	39.13	32.21	96.29	70.24	35.97

smaller standard deviations in comparison to the sample means than the other measures of regional industrial dominance. The relative lack of variation may detract from the stability of the measure in regression analyses. In addition, the sample means of the Gini coefficients are more stable over time than the other dominance indicators, even allowing for their smaller relative variances. This suggests that the declines in dominance as indicated by the absolute measures may be due as much to changes in the scale of the study industries in individual regions as to changes in the firm size distribution. The ordering among the study industries is the same with the Gini coefficient as with the other dominance measures: the measuring and controlling devices industry displays the highest degree of regional dominance or inequality in its regional firm size distributions, and the rubber and plastics industry exhibits a slightly lower level of dominance than metalworking machinery.

Table 6.3 also shows basic descriptive statistics for the agglomeration economy variables. Establishments in the rubber and plastics industry have the lowest average reported values for potential regional labor pooling, as might befit the industry with the smallest labor cost share, although because the agglomeration measure is based on the particular occupations that are the most employed within each industry, it is not precisely comparable across different industries. Measuring and controlling device plants tend to be located in highly innovative regions, with an average regional patenting rate three to five times greater than for the other two study industries. Although the other knowledge spillover measure appears to provide contradictory evidence, with larger figures for proximate relevant academic research expenditures in the rubber and plastics and metalworking machinery industries, this is due to the much sharper spatial decay with which the agglomeration measure is calculated for the measuring and controlling devices industry. For the same reason, it is not useful to contrast the supply pooling variables between measuring and controlling devices and the other two industries. Examining the producer services variable over time, however, reveals a marked drop between 1992 and 1997. This dive likely represents changed purchasing patterns and the shift in the Input-Output coding scheme more than altered regional availability of producer services. A modest increase in producer services follows from 1997 to 2002; the producer services variable uses identical purchasing matrix and coding systems for these two years (see Appendix 5). The inconsistency of variable construction across study years is unavoidable given the available secondary data, and does not affect the cross-sectional analyses.

The control variables are displayed in Table 6.4.[77] There are several observations worth noting. First, the pattern of rising regional industrial dominance revealed in Table 6.3 does not occur in the decade between 1972 and 1982. In fact, the three absolute historic dominance measures register declines in the rubber and plastics and measuring and controlling devices industries. Second, dominance is greater historically in the rubber and plastics industry than in metalworking machinery, the reverse of the current situation. The metalworking machinery industry shows relatively low levels of regional industrial dominance both historically and presently, with little evolution in the characteristic over time. Third, except for metalworking machinery, historic levels of dominance are greater than contemporary levels. Since this statement does not hold for the relative dominance measure, the Gini coefficient, the observation might be explained

[77] The measures of historic dominance and industrial diversity are reported as levels rather than changes over time.

Table 6.4. Control Variables: Descriptive Information.

SIC 30: Rubber and Plastics										
Year / Sample observations		1992 (n = 6,747)			1997 (n = 8,000)			2002 (n = 6,546)		
		mean	std dev	%>mean	mean	std dev	%>mean	mean	std dev	%>mean
Historic Dominance	DH									
Concentratio Ratio		0.5833	0.2122	44.79	0.5466	0.2161	48.79	0.4929	0.2357	46.52
Herfindahl-Hirschman		0.1469	0.1493	27.92	0.1332	0.1376	31.29	0.1139	0.1222	36.04
Rosenbluth		0.0937	0.0959	33.14	0.0834	0.0907	36.53	0.0748	0.0815	36.51
Gini		0.7548	0.0848	50.63	0.7366	0.0800	51.85	0.7199	0.0736	49.54
Unemployment	UE	0.0714	0.0145	52.14	0.0443	0.0135	40.94	0.0566	0.0092	48.41
Income	INC	36,028	4,655	44.60	41,339	5,606	46.95	45,419	6,902	47.63
Population Density	POP	507.5	405.2	40.36	476.7	397.2	37.95	472.1	408.7	35.20
Diversity	DV	0.0147	0.0037	37.02	0.0146	0.0043	37.51	0.0152	0.0055	32.29
Historic Diversity	DVH	0.0139	0.0050	34.62	0.0149	0.0066	35.98	0.0161	0.0078	34.91
SIC 354: Metalworking Machinery										
Year / Sample observations		1992 (n = 5,189)			1997 (n = 5,490)			2002 (n = 4,161)		
		mean	std dev	%>mean	mean	std dev	%>mean	mean	std dev	%>mean
Historic Dominance	DH									
Concentratio Ratio		0.4890	0.2160	50.43	0.5068	0.1995	53.61	0.4940	0.2014	52.75
Herfindahl-Hirschman		0.1031	0.1104	31.41	0.1050	0.1082	27.65	0.1048	0.1089	34.68
Rosenbluth		0.0568	0.0766	33.11	0.0585	0.0783	31.46	0.0557	0.0721	30.59
Gini		0.7401	0.0926	63.58	0.7502	0.0975	63.08	0.7504	0.0911	59.31
Unemployment	UE	0.0752	0.0167	50.16	0.0426	0.0087	59.02	0.0575	0.0079	49.34
Income	INC	36,088	4,365	48.66	41,967	4,961	51.69	45,518	6,091	48.91
Population Density	POP	506.7	351.1	46.68	499.2	355.3	44.77	491.6	361.6	41.82
Diversity	DV	0.0153	0.0038	42.57	0.0145	0.0035	49.31	0.0147	0.0047	46.14
Historic Diversity	DVH	0.0153	0.0071	38.77	0.0156	0.0075	39.03	0.0157	0.0058	38.84
SIC 382: Measuring and Controlling Devices										
Year / Sample observations		1992 (n = 1,384)			1997 (n = 1,540)			2002 (n = 1,201)		
		mean	std dev	%>mean	mean	std dev	%>mean	mean	std dev	%>mean
Historic Dominance	DH									
Concentratio Ratio		0.7396	0.1595	51.73	0.6960	0.1687	41.30	0.6459	0.1803	42.38
Herfindahl-Hirschman		0.2596	0.2099	29.91	0.2070	0.1704	32.40	0.1728	0.1565	31.81
Rosenbluth		0.1676	0.1530	34.68	0.1433	0.1382	35.84	0.1205	0.1244	38.47
Gini		0.8169	0.0773	63.44	0.8051	0.0824	62.27	0.7908	0.0726	59.78
Unemployment	UE	0.0731	0.0133	57.30	0.0431	0.0084	47.14	0.0575	0.0105	40.97
Income	INC	39,442	4,448	53.18	45,485	5,234	54.29	51,215	6,751	48.38
Population Density	POP	681.9	390.0	45.66	677.3	391.0	42.34	698.6	396.7	42.63
Diversity	DV	0.0134	0.0019	39.60	0.0130	0.0021	26.75	0.0131	0.0024	44.96
Historic Diversity	DVH	0.0126	0.0031	36.13	0.0127	0.0035	35.71	0.0134	0.0032	40.30

Note: Historic dominance and diversity reported as levels for 20 years prior (15 years for historic diversity for 1992 samples), rather than the changes over time used in regressions.

by the growth and subsequent decline in the quantity of manufacturing establishments and employment during the time periods in question. Lastly, the regions surrounding measuring and controlling device establishments tend to have substantially greater household income and population density and slightly greater industrial diversity than the regions housing the other two study industries, fitting with the aforementioned geographic concentration of the industry in relatively dense and urbanized areas.

6.4. Variable Correlations

One of the more difficult preparatory tasks in this study was to devise measures of potential agglomeration economies and relevant regional controls that operationalize the ideas in a conceptually valid manner yet are not overly multicolinear with each other. As noted in section 5.7, this is a common challenge for empirical analyses involving multiple agglomeration economy indicators. In this case, the most severe colinearity issues arise among the agglomeration economy measures and in the relationship between industry scale and regional industrial dominance.

As Table 6.5 demonstrates, the five agglomeration economy variables are sufficiently distinct from one another to include simultaneously in the regression analyses. They do evidence substantial correlations, nearly all positive. This is expected and ironically even serves as a further verification of the concept validity of the measures. The correlation coefficient between the two supply pooling measures, manufactured inputs and producer services, exceeds 0.65 in each of the nine industry-year samples and reaches as high as 0.77 in the 2002 rubber and plastics sample. Academic research is associated with the manufactured inputs supply pooling measure as

Table 6.5. Pearson Pairwise Correlation Coefficients Among Agglomeration Variables.

SIC 30: Rubber and Plastics

		1992				1997				2002			
		LP	SP	SD	RS	LP	SP	SD	RS	LP	SP	SD	RS
Labor Pooling	LP												
Manufactured Inputs	SP	0.1577				0.0207				-0.0144			
Producer Services	SD	-0.5016	0.6712			-0.4764	0.7617			-0.5395	0.7651		
Research	RS	0.1602	0.7670	0.4983		0.1587	0.6757	0.4362		0.1165	0.6861	0.4470	
Patenting	PS	-0.0479	0.4774	0.3651	0.3492	0.0167	0.4200	0.3910	0.2913	-0.0215	0.4486	0.3687	0.3085

SIC 354: Metalworking Machinery

		1992				1997				2002			
		LP	SP	SD	RS	LP	SP	SD	RS	LP	SP	SD	RS
Labor Pooling	LP												
Manufactured Inputs	SP	0.6153				0.3716				0.1527			
Producer Services	SD	0.0638	0.6214			-0.3327	0.6482			-0.5148	0.6486		
Research	RS	0.0014	0.5203	0.4767		0.0701	0.5551	0.3628		0.0081	0.5523	0.3291	
Patenting	PS	0.5222	0.4350	0.2830	0.0577	0.2635	0.4670	0.3422	0.0435	0.1596	0.4547	0.3125	-0.0216

SIC 382: Measuring and Controlling Devices

		1992				1997				2002			
		LP	SP	SD	RS	LP	SP	SD	RS	LP	SP	SD	RS
Labor Pooling	LP												
Manufactured Inputs	SP	0.6064				0.6540				0.5817			
Producer Services	SD	0.1661	0.6837			0.2071	0.6576			0.1074	0.6891		
Research	RS	0.2686	0.6529	0.5253		0.3120	0.6200	0.5239		0.3308	0.5937	0.5285	
Patenting	PS	0.5319	0.5230	0.1252	0.3936	0.5748	0.5531	0.0990	0.4006	0.6622	0.5705	0.1545	0.4439

Note: Correlations measured with natural logarithms of all agglomeration variables except for labor pooling.

well, again the most strongly for rubber and plastics manufacturers, with correlation coefficients ranging from 0.67 to 0.77.[78] Although there is sufficient independent variation for regression analysis, the high correlations suggest that the estimated coefficients be evaluated with caution as there may be substantial overlap among the impacts of these variables.

The only sizeable negative correlations are between potential labor pools and producer services, occurring in five of the nine samples, indicating that the study industries do not tend to employ many workers within the same occupational categories as producer services employees. On the other hand, the consistently positive association between academic research and manufactured inputs implies that supplier industries may benefit from proximity to the same types of research activity as do the sample establishments. Interestingly, though patenting is positively correlated with manufactured inputs in each of the samples, in only four of the samples, three of them representing measuring and controlling devices, is patenting substantially positively associated with potential labor pools. If patents in relevant technology classes are granted primarily within the immediate region of the sample establishments, then the relatively steep distance decay used to construct the labor pooling measure for the measuring and controlling devices industry may have focused the labor pooling measure on the same nearby counties to a greater degree than for the other two study industries.

Regional industrial dominance tends to be highly negatively correlated with the size of the local industry. To some degree, this correspondence occurs because the concepts overlap. Just as the idea of economic dominance by a single industry has less purchase within a large, diverse economy, so too is the notion of regional industrial

[78] Perhaps this is due to colocation along the product chain over time in this mature industry.

dominance more readily applied to a smaller, more isolated region. Intuitively, is it easier to dominate a smaller industry in the sense that there are fewer competitors and it requires less absolute size or resources to achieve a particular threshold of dominance. The problem is that the association makes it difficult to separate the effects of dominance from industry size in an empirical analysis. This is a pervasive problem in econometric studies of industrial concentration at the national scale as well (Hay and Morris 1991, p. 205). The theory presented in Chapter Three provides support to a dominance interpretation by elucidating particular mechanisms by which dominance may influence firm performance. Although the causal link between industry size and establishment productivity is itself less than perfectly clear (see section 2.4.2.2), it is helpful to distinguish empirically the impacts of regional industrial dominance from effects due solely to the size of the local industry as much as possible.

Table 6.6 illustrates the relationship between industry size and dominance by reporting the Pearson correlation coefficients of the four indicators of regional industrial dominance with two measures of local industry scale, employment and the number of firms (both in logarithms). For the majority of the nine industry-year samples, the five-firm concentration ratio measure covaries almost as the opposite of industry scale as measured by the firm count; the relationship holds in the same direction but not as strongly with industry employment. In the context of interpreting regression results, it would be problematic to determine whether it is industrial concentration or local industry size that affects establishment productivity.

This obstacle provides an additional incentive for exploring multiple ways of measuring regional industrial dominance in this study. If alternative dominance measures

Table 6.6. Pearson Correlation Coefficients Between Dominance and Industry Scale Measures.

SIC 30: Rubber and Plastics							
		1992		1997		2002	
Dominance		Firms	Employment	Firms	Employment	Firms	Employment
Concentratio Ratio	D_C	-0.8936	-0.7687	-0.8984	-0.8012	-0.9057	-0.7795
Herfindahl-Hirschman	D_H	-0.6657	-0.5259	-0.6550	-0.5683	-0.7437	-0.6222
Rosenbluth	D_R	-0.8163	-0.6830	-0.8504	-0.7347	-0.8459	-0.7057
Gini	D_G	-0.0581	0.0536	0.1019	0.1384	0.2463	0.2871
SIC 354: Metalworking Machinery							
		1992		1997		2002	
Dominance		Firms	Employment	Firms	Employment	Firms	Employment
Concentratio Ratio	D_C	-0.8251	-0.7047	-0.8172	-0.7032	-0.8351	-0.7435
Herfindahl-Hirschman	D_H	-0.6420	-0.5199	-0.5688	-0.4509	-0.6363	-0.5186
Rosenbluth	D_R	-0.7328	-0.6166	-0.7184	-0.6134	-0.6990	-0.5763
Gini	D_G	0.2598	0.4170	0.2163	0.3596	0.2969	0.4152
SIC 382: Measuring and Controlling Devices							
		1992		1997		2002	
Dominance		Firms	Employment	Firms	Employment	Firms	Employment
Concentratio Ratio	D_C	-0.8235	-0.6559	-0.7675	-0.6289	-0.6091	-0.3462
Herfindahl-Hirschman	D_H	-0.6154	-0.4100	-0.5587	-0.4161	-0.4787	-0.2587
Rosenbluth	D_R	-0.7559	-0.5625	-0.8040	-0.6380	-0.7800	-0.5491
Gini	D_G	0.0467	0.2447	0.3477	0.4721	0.4331	0.6161

Note: Correlations measured with natural logarithms of firm and employment totals.

that are less closely related to industry scale demonstrate influences on productivity in accordance with those estimated for the concentration ratio indicator, then the effects may be more securely attributed to dominance rather than industry size. The correlations among the dominance measures are displayed in Table 6.7. The three absolute measures—concentration ratio, Herfindahl-Hirschman index, and Rosenbluth index—are closely associated with each other, whereas the Gini coefficient is positively correlated with the other measures of regional industrial dominance but not nearly as strongly.

Table 6.7. Pearson Pairwise Correlation Coefficients Among Dominance Measures.

		1992			1997			2002		
SIC 30: Rubber and Plastics										
		D_C	D_H	D_R	D_C	D_H	D_R	D_C	D_H	D_R
Concentratio Ratio	D_C									
Herfindahl-Hirschman	D_H	0.8409			0.8491			0.8929		
Rosenbluth	D_R	0.8761	0.8954		0.8991	0.8460		0.9099	0.9306	
Gini	D_G	0.4444	0.5401	0.3112	0.2808	0.4379	0.1507	0.1191	0.2756	0.0675
SIC 354: Metalworking Machinery		1992			1997			2002		
		D_C	D_H	D_R	D_C	D_H	D_R	D_C	D_H	D_R
Concentratio Ratio	D_C									
Herfindahl-Hirschman	D_H	0.8951			0.8541			0.8509		
Rosenbluth	D_R	0.8217	0.8582		0.7872	0.8472		0.8139	0.9269	
Gini	D_G	0.2772	0.3995	0.1201	0.3300	0.4881	0.1601	0.2093	0.3681	0.1693
SIC 382: Measuring and Controlling Devices		1992			1997			2002		
		D_C	D_H	D_R	D_C	D_H	D_R	D_C	D_H	D_R
Concentratio Ratio	D_C									
Herfindahl-Hirschman	D_H	0.8651			0.8722			0.9079		
Rosenbluth	D_R	0.8629	0.9514		0.8745	0.8604		0.8955	0.8894	
Gini	D_G	0.4894	0.6445	0.4538	0.2886	0.4572	0.1367	0.4077	0.4830	0.1556

Returning to Table 6.6, the Rosenbluth index, emphasizing the smaller end of the size distribution, is highly negatively correlated with regional industry scale, but not as much so as the concentration ratio. The Herfindahl-Hirschman index displays much lower levels of correlation, and the Gini coefficient tends to exhibit a positive but small association with local industry size.

Employing alternative dominance measures is only one approach taken in this study to address the issue of the close relationship between regional industrial dominance and industry scale. The four non-relative agglomeration economy variables, along with regional population density, help account for the impacts of regional industry scale in the production function. Additional tests involving size controls, altered samples, and variable substitutions are described in section 7.5.

Finally, it is interesting to examine how closely the five agglomeration economy variables correspond to more basic urbanization and localization measures, to place the results of this analysis in perspective with respect to previous agglomeration economies work as described in section 2.4.2.2. Table 6.8 demonstrates that producer services is related to population density for two of the three study industries, whereas manufactured inputs and patenting are more closely associated with industry employment. Academic research is proxied better by population density for the metalworking machinery samples, by industry employment for measuring and controlling devices, and almost equally by the urbanization and localization indicators within the rubber and plastics samples. Labor pooling, as a relative measure, varies widely in its relationship to urbanization and localization. These results support the conclusions Feser (1997) reaches in a similar comparison of specialized agglomeration measures with simpler urbanization and localization proxies: both urbanization and localization contribute to the composition of agglomeration economies, and the extent to which each proxy is associated with different agglomeration benefits varies across industries.

6.5. Summary

This chapter examined the characteristics of the study samples and independent variables used in the analysis. All of the study industries are spatially concentrated in dense, well-populated regions, but the measuring and controlling devices industry is concentrated to a greater degree than the other two industries. Regional industrial

Table 6.8. Pearson Correlation Coefficients Between Agglomeration Variables and Urban and Industry Scale.

SIC 30: Rubber and Plastics		1992		1997		2002	
		Population Density	Industry Employment	Population Density	Industry Employment	Population Density	Industry Employment
Labor Pooling	LP	-0.3828	-0.0357	-0.3008	0.1018	-0.3493	0.0643
Manufactured Inputs	SP	0.5973	0.6299	0.6617	0.5600	0.6851	0.5835
Producer Services	SD	0.7998	0.5148	0.7923	0.5006	0.7843	0.4717
Research	RS	0.4120	0.3978	0.4092	0.4246	0.4528	0.4348
Patenting	PS	0.4439	0.5546	0.4742	0.5617	0.5102	0.5844
SIC 354: Metalworking Machinery		1992		1997		2002	
		Population Density	Industry Employment	Population Density	Industry Employment	Population Density	Industry Employment
Labor Pooling	LP	0.2396	0.7209	-0.0892	0.4917	-0.2695	0.2952
Manufactured Inputs	SP	0.5837	0.6076	0.5861	0.5590	0.6099	0.5604
Producer Services	SD	0.7511	0.2558	0.7406	0.2584	0.7515	0.2861
Research	RS	0.3178	0.0175	0.2808	0.0759	0.2504	0.0815
Patenting	PS	0.3902	0.7107	0.4913	0.7170	0.4877	0.7134
SIC 382: Measuring and Controlling Devices		1992		1997		2002	
		Population Density	Industry Employment	Population Density	Industry Employment	Population Density	Industry Employment
Labor Pooling	LP	-0.0609	0.4633	-0.1341	0.4768	-0.1929	0.4053
Manufactured Inputs	SP	0.0498	0.5220	-0.0108	0.5866	0.0755	0.5114
Producer Services	SD	0.2815	0.2541	0.2691	0.2818	0.3266	0.2423
Research	RS	0.1891	0.4472	0.1504	0.4489	0.1306	0.3164
Patenting	PS	0.0078	0.6155	-0.0581	0.6389	-0.0438	0.6403

Note: Correlations measured with natural logarithms of all variables except for labor pooling.

dominance, as measured by absolute indicators, has risen across the three study years, but is at lower levels than experienced twenty years earlier in both the rubber and plastics and the measuring and controlling devices industries. The Gini coefficient acts quite differently than the other three measures of regional industrial dominance, with less variation across regions and greater stability over time. The trends observed make it evident that the three study industries diverge in terms of attributes and changes over time.

There are several caveats and cautions that pertain to the study samples and the examination of descriptive statistics. First, because the estimation samples are essentially incomplete censuses rather than random draws, inferential statistics are less important than for a typical regression analysis. Second, LRD administrative records constitute the largest portion of establishments excluded from the samples. Therefore, the results of the quantitative analysis should be construed as applying to the set of industry establishments that does not include the smallest manufacturers. Lastly, though the agglomeration and control variables are conceptually and statistically distinct, some of them covary closely enough to merit caution in interpreting their effects independently.

With the observations in this chapter as background, the next chapter turns to the principal findings of this study from the regression analysis of establishment-level production and cost share functions.

CHAPTER SEVEN: DOMINANCE, AGGLOMERATION, AND PRODUCTIVITY

7.1. Introduction

The text up to this point has laid the groundwork for the empirical analysis of establishment-level productivity, posing the research questions and building from the theoretical framework and empirical model through to the sample selection and variable construction. This chapter presents the primary results of the dissertation, including the implications of the model estimations for the two research questions posed in Chapter One. There is substantial support for the first hypothesis that regional industrial dominance negatively influences the productivity of manufacturing establishments, but the bulk of the evidence opposes the second hypothesis that the influence of regional industrial dominance on production is due to limitations on the ability of firms to take advantage of localized agglomeration economies.

The chapter starts by detailing several technical aspects of the modeling process, including model diagnostics and tests of possible functional simplifications. The main focus is then placed on exhibiting the regression results from the production model and interpreting them with regard to the effects of regional industrial dominance and agglomeration economies on establishment productivity. The last portion considers the implications of estimating the models with several substitute measures of regional industrial dominance.

7.2. Model Tests and Functional Restrictions

The system of equations consisting of the translog production function (equation 5.20) and three associated cost share equations (equation 5.21) is estimated jointly using iterated nonlinear seemingly unrelated regression. Hypothesis tests are carried out using the Wald, Lagrange multiplier, and likelihood ratio test statistics. These three tests are identical if the log-likelihood function is quadratic and are asymptotically equivalent if it is not, with the differences among them depending on the specific departure of the log-likelihood curve from the quadratic form (Berndt and Savin 1977; Buse 1982).[79] In many economic applications, the Wald test tends to be the most likely, and the likelihood ratio the least likely, to reject hypotheses (Berndt 1991). For the tests conducted as part of this study, the substantive conclusions are in almost every case the same with each of the three statistics. Only the likelihood ratio test results are reported unless otherwise noted.

The model is estimated in close to its most extended form, with no restrictions on the production function, with interactions included between dominance and the agglomeration economies, and with the dominance and agglomeration variables specified as factor-augmenting. Preliminary specifications also included cross-terms among the agglomeration economy variables. These terms are dropped from the preferred specification because they are almost always insignificant, the hypothesis that they are jointly equal to zero cannot be rejected, and their exclusion does not appreciably change the estimated coefficients for the other parameters.

The model is estimated using iterated nonlinear seemingly unrelated regression, as described in section 4.5. Alternative starting values test model convergence, leading to

[79] The likelihood ratio test is the most computationally demanding, as it uses both the restricted and unrestricted parameter estimates. The Wald test is based on the unrestricted estimate only and the Lagrange multiplier is calculated using only the restricted estimate.

the conclusion that the optima achieved are robust within a reasonably large domain but are not global. The nonlinear nature of the equations and the complexity of the modeling system ensure local rather than universal extrema, and caution is recommended in applying the estimation results to points distant from the sample means. In other words, the estimated models are most accurate for values of the independent variables that fall well within the ranges observed in the samples. As for residual normality, statistical normality tests are not appropriate for large sample sizes (roughly, greater than 1,000 observations) because they tend to detect small deviations from normality that are statistically significant but practically unimportant (Thode 2002).[80] In addition, larger samples make the estimation procedure more robust to departures from normality. Instead, the residuals are tested for normality graphically using residual histograms and normal quantile plots. Those diagnostic devices illustrate that the residuals from the four model equations follow distributions that are reasonably close to normal. Although there is some excess kurtosis, particularly in the capital cost share equation, it is not enough to challenge the validity of the estimation method. Moreover, since the study samples are closer to censuses than random samples, inference is not an issue of overriding importance.

Breusch-Pagan tests conducted under several different assumptions about the form of possible heteroskedasticity suggest that there may be substantial heteroskedasticity in the error terms. Uncorrected heteroskedasticity may lead to underestimated standard errors and exaggerated coefficient significance levels. These outputs are less crucial to this analysis than in studies that aim to establish generalizations

[80] The MODEL procedure in SAS offers the Shapiro-Wilks and Kolmogorov-Smirnov univariate normality tests.

to larger populations. Even the modified version of the Breusch-Pagan test is susceptible to deviations from normality in large estimation samples and may simply be picking up these divergences.[81] Nevertheless, it is worth attempting to assess the severity of the problem. As there are no suitable instrumental variables available (see section 4.7), heteroskedasticity-corrected standard errors are computed for each model permutation using the third of the formulations suggested by Davidson and MacKinnon (1993).[82] The corrections greatly alter the estimated standard errors of the terms involving the standard inputs, generally reducing the significance levels of these variables. In particular, coefficients involving the energy variable tend to become insignificant. These results are questionable in light of the outcomes of previous production function work, including that using the LRD. Yet the standard errors pertaining to the remaining coefficients, including those measuring the influences of dominance, agglomeration, and the control variables, change relatively little. Most of the significance levels of the estimated parameters other than those involving capital, labor, energy, or materials adjust by only a few percent. A few of the estimated standard errors even decrease. Because the primary results of interest are not substantively altered, the uncorrected original models are presented in the text. The heteroskedasticity-corrected versions of the main models

[81] The modified Breusch-Pagan test is more powerful than the unmodified version in the absence of normality but remains sensitive to the normality assumption (Greene 2003, p. 224). The Breusch-Pagan test results are available from the author. White's test for heteroskedasticity is also sensitive to non-normality and is inappropriate in this case given the inclusion of squared and product terms in the translog production function.

[82] Long and Ervin (2000) find the third, pseudo-jackknife, option to be superior using Monte Carlo simulations. In this study, the differences among the results obtained using the White (1980) correction and the three formulations by Davidson and MacKinnon (1993) are negligible.

employing the concentration ratio measure of regional industrial dominance are contained in Appendix 7.[83]

The next step is to test several possible types of model restrictions. The test results are displayed in Table 7.1. The dominance and agglomeration economy variables are specified entering the production function in factor-augmenting form, as the most general approach. It is more common in translog studies to specify independent variables other than the standard production inputs as Hicks-neutral for model simplicity and computational ease. Earlier research testing for Hicks neutrality has produced mixed results (described in section 4.2.1). The sample sizes in this analysis are sufficient to support estimation of the additional cross-term variables, so Hicks neutrality should be imposed only if justified by the data. The test for Hicks neutrality, introduced in section 4.5, is that, for the variable k, the coefficients λ_{ik} are equal to zero for each standard input i.

For labor pooling and the two knowledge spillover variables, Hicks neutrality is rejected at the 90 percent confidence level in each of the nine industry-year models. The Hicks neutrality of regional industrial dominance can also be rejected in all but one case, measuring and controlling devices in 2002. There is more variety in the results for manufactured inputs and producer services across the different years and industries, but a majority of the models favor factor augmentation by the two supply pooling variables. To maintain ready comparisons across all of the variables and samples, the factor-augmenting form is retained for regional industrial dominance and all five agglomeration variables.

[83] Heteroskedasticity-corrected versions of the models with alternative dominance variables are available from the author.

Table 7.1. Tests of Model Restrictions.

SIC	30			354			382		
Industry	rubber & plastics			metalworking machinery			measuring & controlling devices		
Year	1992	1997	2002	1992	1997	2002	1992	1997	2002
Hicks-Neutrality Tests									
Dominance	44.52	13.25	14.50	31.40	43.39	26.15	21.70	15.30	4.53
	(0.000)	(0.010)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.339)
Labor Pooling	14.60	80.24	111.42	10.32	16.45	44.08	71.74	11.93	17.30
	(0.006)	(0.000)	(0.000)	(0.035)	(0.002)	(0.000)	(0.000)	(0.018)	(0.002)
Manufactured Inputs	19.40	7.37	1.97	27.97	2.77	7.80	39.84	3.40	17.59
	(0.001)	(0.118)	(0.741)	(0.000)	(0.597)	(0.099)	(0.000)	(0.494)	(0.001)
Producer Services	23.23	7.54	5.03	49.94	3.44	31.27	21.00	3.16	16.74
	(0.000)	(0.110)	(0.284)	(0.000)	(0.487)	(0.000)	(0.000)	(0.532)	(0.002)
Research	44.69	69.12	57.16	50.54	58.15	38.41	18.82	16.40	11.97
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.003)	(0.018)
Patents	24.89	43.61	41.49	8.94	18.47	8.57	9.41	8.31	13.43
	(0.000)	(0.000)	(0.000)	(0.063)	(0.001)	(0.073)	(0.052)	(0.081)	(0.009)
Dominance-Agglomeration	5.95	5.56	22.77	6.35	9.00	9.80	4.86	4.88	17.57
Interaction Terms	(0.311)	(0.352)	(0.000)	(0.274)	(0.109)	(0.081)	(0.433)	(0.430)	(0.004)
Technology Properties									
Homotheticity	218.31	247.94	718.42	145.33	164.69	400.55	35.96	63.11	41.06
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Homogeneity	232.58	330.82	820.30	156.35	182.86	440.16	18,346	76.52	61.39
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant Returns to Scale	450.50	551.08	1,015.0	224.58	290.37	537.91	24,509	149.31	141.22
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Functional Simplifications									
CES	75.55	100.14	53.32	85.38	77.44	6.80	6.28	10.66	14.20
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2356)	(0.2804)	(0.0586)	(0.0144)
Cobb-Douglas	79,106	99,547	72,025	63,451	74,871	44,755	12,125	15,443	8,537.3
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Note: All statistics derived from likelihood ratio tests except that the CES test uses the Wald statistic; figures in parentheses are probability values.

The flexible translog functional form does not require the imposition of homotheticity, homogeneity, or constant returns to scale (linear homogeneity), but instead allows these technology conditions to be tested as hypotheses. The test procedures for these production technology assumptions were presented earlier in the context of the production function model (see section 4.5, equations 4.11 through 4.13). If one or more of these properties is upheld empirically, then applying it as a restriction on the model may serve as a helpful simplification, improving estimation efficiency. The three technology conditions are nested: homogeneity is stricter than homotheticity, and constant returns to scale implies both homogeneity and homotheticity. In a study using 1992 LRD data (but a smaller sample derived with somewhat different construction procedures), Feser (2002) finds that homotheticity and homogeneity do apply to the measuring and controlling devices sector, and constant returns to scale can be rejected only weakly. All three properties are upheld for an industry not considered in this study, the manufacture of farm and garden machinery and equipment. In the current analysis, however, each of the three conditions of homotheticity, homogeneity, and constant returns to scale is strongly rejected in each model. The reason for the discrepancy with Feser's earlier result is not apparent, though hypotheses are easier to deny with larger samples.

Table 7.1 also shows the results of tests for the simpler Cobb-Douglas and CES functional forms that are encompassed by the translog specification. These tests are described in sections 4.3 and 4.5. Because the CES test entails an alternative specification of the translog function in which the restricted parameter estimates fail to converge using the study samples, the Wald statistic is displayed in place of the likelihood ratio. The Cobb-Douglas equation, a major simplification of the translog form, is strongly rejected in each case. The CES formulation is rejected strongly in six of the nine models, and rejected weakly in one more. The CES offers a reasonably similar specification to the translog for the 1992 measuring and controlling devices and the 2002 metalworking machinery models. Nevertheless, it is clear that the Cobb-Douglas and CES specifications do not in general suffice to model the relationships indicated by the application of the translog form.

As mentioned earlier in this section, interactions among the agglomeration variables are omitted because they do not substantially impact the estimation results of interest. In contrast, the interaction terms between dominance and agglomeration economies are central to the research at hand. They constitute the principal evidence for assessing the second research hypothesis posed in Chapter One, that regional industrial dominance limits the abilities of firms to improve their economic productivity by taking advantage of local agglomeration possibilities. Joint tests on the significance of the interactions between dominance and agglomeration, however, yield weak results. Only in the 2002 models are the five interaction terms jointly significant at the 90 percent confidence level, suggesting that dominance may not have had important effects on the availability of agglomeration benefits until relatively recently. Because of the importance of these terms to one of the chief hypotheses of the study, they are retained in each model and are examined in more depth in section 7.3.6.

7.3. Modeling Results

One of the characteristic features of the translog production function is the large quantity of coefficient estimates it produces by including numerous quadratic and interaction terms. For convenience, Table 7.3 reproduces the variables and associated coefficients from the full production function model of equation 5.20. The main model results begin with diagnostics in Table 7.2 and continue with coefficient estimates, asymptotic standard errors, and associated probability values obtained using the concentration ratio measure of dominance presented in Tables 7.4 through 7.6. All non-dummy independent variables are mean centered so that the estimated parameters refer to the effects at the sample means of the other variables. The standard inputs, the agglomeration economy variables other than labor pooling, and income and population density are transformed by natural logarithms and thus their coefficients may be interpreted directly as elasticities at the sample means. As is standard in cross-sectional work, the estimated parameters are interpreted as representing a long-run equilibrium.

Tables 7.4 through 7.6 display adjusted R^2 values for each of the four model equations. These figures are included mainly for completeness rather than for judging among model specifications since the goodness-of-fit statistic is not guaranteed to be well-behaved for nonlinear equations or in a multiple equation system (Basmann 1962; Greene 2003, pp. 209, 345). They may, however, be taken as an indication of the general fit of the model to the data and the primacy of the production function in the system estimation. The results tables also contain the generalized system-wide R^2 statistic suggested by Berndt (1991, p. 468), though for this analysis its narrow empirical range (all values fall between 0.998 and 1) lends it little utility.

7.3.1. Production Function Regularity Conditions

Assessments of monotonicity and convexity are displayed in Table 7.2. They suggest that the economic regularities required for well-behaved production function behavior are satisfied at the point of approximation. Monotonicity holds at the sample means in each model, and convexity does as well with only one exception, measuring and controlling devices in 1997. With regard to the actual data points in the nine samples, though monotonicity is satisfied at the large majority of the observations, with most violations occurring with respect to just one of the four standard inputs, the isoquant

Table 7.2. Regularity Conditions and Returns to Scale.

SIC	30			354			382		
Industry	rubber & plastics			metalworking machinery			measuring & controlling devices		
Year	1992	1997	2002	1992	1997	2002	1992	1997	2002
Sample observations	6,747	8,000	6,546	5,189	5,490	4,161	1,384	1,540	1,201
Monotonicity									
Sample means	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations (percent)	90.41	91.85	91.86	91.83	91.79	90.53	90.61	87.99	90.93
Standard inputs (percent)	97.46	97.85	97.89	97.91	97.79	97.52	97.56	96.87	97.71
"Near" Monotonicity									
Sample means	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations (percent)	90.58	92.03	91.98	91.97	91.99	90.65	90.97	88.71	91.10
Standard inputs (percent)	97.50	97.89	97.92	97.95	97.84	97.55	97.65	97.05	97.75
Convexity									
Sample means	yes	yes	yes	yes	yes	yes	yes	no	yes
Observations (percent)	49.94	47.71	49.08	33.62	27.55	33.09	40.14	33.68	43.18
"Near" Convexity									
Sample means	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations (percent)	76.56	79.17	84.51	72.35	78.44	82.99	70.40	81.77	87.85
Returns to scale									
Estimate at sample means	0.9375	0.9415	0.9354	0.9711	0.9577	0.9466	0.9091	0.9070	0.8984
(Probability value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

convexity criterion fails for a much larger proportion of sample. This result is not unexpected: as noted in section 4.6, factor-augmenting independent variables make it difficult to affirm the convexity criterion due to the number and complexity of the terms involving the standard inputs in the production function. Allowing an error distance to account for evaluating the convexity criterion as a function of estimated parameters that incorporate estimation error, the proportion of data points at which convexity “nearly” holds is much larger, roughly 75 or 80 percent. Overall, the parameter estimates obtained are most reliable in the neighborhood of the point of estimation. Caution is warranted in applying the results to more distant points in the sample spaces.

7.3. Variables and Coefficients in Translog Production Function Model.

Coefficient	Variable	Description	Coefficient	Variable	Description
α_0		constant	λ_{lpk}	LP · ln K	
α_k	ln K	capital	λ_{lpl}	LP · ln L	
α_l	ln L	labor	λ_{lpe}	LP · ln E	
α_e	ln E	energy	λ_{lpm}	LP · ln M	
α_m	ln M	materials	λ_{spk}	ln SP · ln K	
β_{kk}	(ln K)^2		λ_{spl}	ln SP · ln L	
β_{ll}	(ln L)^2		λ_{spe}	ln SP · ln E	
β_{ee}	(ln E)^2		λ_{spm}	ln SP · ln M	
β_{mm}	(ln M)^2		λ_{sdk}	ln SD · ln K	agglomeration-
β_{kl}	ln K · ln L	quadratic input	λ_{sdl}	ln SD · ln L	input
β_{ke}	ln K · ln E	interaction terms	λ_{sde}	ln SD · ln E	interaction terms
β_{km}	ln K · ln M		λ_{sdm}	ln SD · ln M	
β_{le}	ln L · ln E		λ_{rsk}	ln RS · ln K	
β_{lm}	ln L · ln M		λ_{rsl}	ln RS · ln L	
β_{em}	ln E · ln M		λ_{rse}	ln RS · ln E	
γ_d	D	dominance	λ_{rsm}	ln RS · ln M	
γ_{lp}	LP	labor pooling	λ_{psk}	ln PS · ln K	
γ_{sp}	ln SP	manufactured inputs	λ_{psl}	ln PS · ln L	
γ_{sd}	ln SD	producer services	λ_{pse}	ln PS · ln E	
γ_{rs}	ln RS	research	λ_{psm}	ln PS · ln M	
γ_{ps}	ln PS	patenting	v_{de}	DE	dominator
δ_{dd}	D^2	dominance squared	v_{se}	SE	dominated
δ_{dlp}	D · LP		v_{cr1}	CR1	South
δ_{dsp}	D · ln SP	dominance-	v_{cr2}	CR2	Midwest
δ_{dsd}	D · ln SD	agglomeration	v_{cr3}	CR3	West
δ_{drs}	D · ln RS	interaction terms	v_{pop}	ln POP	population density
δ_{dps}	D · ln PS		v_{ue}	UE	unemployment
λ_{dk}	D · ln K		v_{inc}	ln INC	income
λ_{dl}	D · ln L	dominance-input	v_{dv}	DV	diversity
λ_{de}	D · ln E	interaction terms	ρ_{dh}	DH	historic dominance
λ_{dm}	D · ln M		ρ_{dvh}	DVH	historic diversity

7.3.2. Returns to Scale

Although it is not a focus of this research, returns to scale are worth examining at least briefly as a means to illustrate some of the differences between this research and previous micro-level production function studies. Internal returns to scale are estimated to be significantly less than unity for all four samples at the sample means, though the estimates are not far below the level of constant returns in substantive terms (Table 7.2). This result accords with the stark rejection of linear homogeneity discussed in section 7.2 but contradicts the consensus view from earlier studies that constant or even increasing returns to scale are the norm at the microeconomic level (Nguyen and Reznek 1990; Kim 1995; Klette and Griliches 1996; Feser 2001a; Nguyen and Lee 2002).[84] Klette and Griliches (1996) contend that using a value-based measure of output may downward bias estimates of economies of scale to the extent that imperfect price competition urges firms with an efficiency advantage to undercut competitors' prices in order to expand market share. As argued in section 5.10, however, the assumption of profit-maximizing behavior is reasonable in the context of individual establishments and within the particular study industries, and departures from this assumption need not occur only in the direction of a downward bias.

There are at least three ways in which this analysis departs from the work of earlier researchers that may explain the estimates of decreasing internal returns to scale. First, the omission of administrative records causes the very smallest manufacturing plants to be excluded from the samples. This may influence the findings with regard to internal returns to scale at the aggregate industry level.[85] Second, the production function is not restricted to being homothetic and homogeneous. Strictly defined, internal returns to scale refer to the proportion by which plant outputs change in response to changes in the quantity of inputs, keeping factor proportions stable. In this study, factor proportions are permitted to vary both with respect to standard input quantities and with levels of

[84] Baldwin *et al*. (2007), however, report very similar returns to scale estimates in a micro-level analysis of Canadian manufacturers.

[85] Nguyen and Reznek (1990), Feser (2001a), and Nguyen and Lee (2002) also omit administrative records.

dominance and potential agglomeration economies.

The most plausible explanation comes from the fact that estimated internal returns to scale differ with the point of estimation. This is fitting in research that, unlike previous studies, includes and indeed focuses on the effects of relative establishment size. Because of the right-skewed establishment size distribution of the industry samples, internal returns to scale calculated at the sample means (as presented in Table 7.2) is more closely representative of the larger rather than the smaller plants. A recalculation for smaller ranges of standard inputs yields estimates of constant or increasing returns to scale, more in line with earlier work. Moreover, regressions performed separately on the three establishment dominance categories—dominators, dominated plants, and neither dominator nor dominated—for each industry-year combination yield estimates of increasing or constant returns to scale at the sample mean for those plants that are part of dominator firms and decreasing returns to scale for the other two establishment classifications. In other words, internal returns to scale diminish with rising input quantities holding relative size constant, but establishments that are relatively small within a regional industry tend to have lower internal returns to scale than larger firms.

7.3.3. Standard Inputs and Control Variables

Tables 7.4 through 7.6 present the estimates of the production function and factor share system for the rubber and plastics, metalworking machinery, and measuring and controlling devices industries for the years 1992, 1997, and 2002. The first item to notice is that the coefficients of the standard inputs and cross-terms (the α and β terms) display the expected signs. Production is positively related to input quantities, and negative cross-products indicate input substitution in each of the nine models.[86]

Turning next to the control variables, there is a lot of variance in the estimated coefficients across the three industries and in some cases over the three study years as well. Higher regional median household incomes are associated with greater productivity in the rubber and plastics industry, where income may indicate local workforce skills (income is highly correlated with workforce education, see section 5.8). The effect is substantial but not overwhelming. Holding all other variables constant, a ten percent increase in median household income from the sample mean is associated with a 1.4 percent rise in output in 1992, and somewhat smaller gains in the latter two study years. Median income has the opposite effect on productivity in the other two study industries, however, and in a couple of instances the estimated impact is quite sizeable. The labor cost share is substantially larger on average in metalworking machinery and measuring and controlling device establishments than in the rubber and plastics industry, perhaps implying that higher wage rates outweigh regional skill advantages for these two manufacturing industries.

Many of the other control variables, including unemployment and industrial diversity, demonstrate contrasts in magnitude and sometimes in sign across the three industries. Differing macroeconomic climates may partially explain the variation in the effect of unemployment over time. For instance, in the rubber and plastics industry, the significant positive influence of unemployment on productivity in 1997 may be due to

[86] Note that this is only a face-value examination of the direct coefficient estimates. Partial elasticity measures, such as Morishima or Allen elasticities, are typically employed to evaluate empirical input substitution (Chambers 1988; Blackorby and Russell 1989). Frondel and Schmidt (2002) argue that substitution elasticities are driven by factor shares in the translog framework and thus are not very informative.

Table 7.4. Parameter Estimates for Rubber and Plastics (SIC 30).

Year	1992				1997				2002			
Variable	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
α_0	8.2778	0.0112	737.21	0.00	8.4360	0.0105	802.26	0.00	8.7876	0.0124	709.27	0.00
α_k	0.1296	0.0007	186.46	0.00	0.1676	0.0007	225.36	0.00	0.1976	0.0010	188.73	0.00
α_l	0.3338	0.0016	204.02	0.00	0.3084	0.0013	236.97	0.00	0.2976	0.0016	187.20	0.00
α_e	0.0272	0.0002	124.16	0.00	0.0226	0.0002	140.21	0.00	0.0220	0.0002	126.40	0.00
α_m	0.4469	0.0020	222.83	0.00	0.4430	0.0017	259.34	0.00	0.4182	0.0020	208.74	0.00
β_{kk}	0.0854	0.0007	129.81	0.00	0.0965	0.0006	151.56	0.00	0.1020	0.0008	128.23	0.00
β_{ll}	0.1421	0.0016	91.12	0.00	0.1380	0.0012	111.34	0.00	0.1188	0.0015	80.39	0.00
β_{ee}	0.0190	0.0002	76.19	0.00	0.0167	0.0002	88.95	0.00	0.0160	0.0002	84.78	0.00
β_{mm}	0.1715	0.0011	154.26	0.00	0.1788	0.0010	173.63	0.00	0.1567	0.0011	141.70	0.00
β_{kl}	-0.0317	0.0006	-48.74	0.00	-0.0329	0.0006	-56.27	0.00	-0.0381	0.0007	-52.42	0.00
β_{ke}	-0.0026	0.0002	-10.88	0.00	-0.0022	0.0002	-12.63	0.00	-0.0035	0.0002	-18.27	0.00
β_{km}	-0.0564	0.0006	-102.16	0.00	-0.0666	0.0005	-123.89	0.00	-0.0731	0.0007	-104.32	0.00
β_{le}	-0.0050	0.0003	-16.38	0.00	-0.0048	0.0002	-22.25	0.00	-0.0030	0.0002	-13.68	0.00
β_{lm}	-0.1142	0.0010	-118.85	0.00	-0.1081	0.0008	-138.45	0.00	-0.0941	0.0009	-101.73	0.00
β_{em}	-0.0123	0.0002	-51.21	0.00	-0.0104	0.0002	-54.84	0.00	-0.0110	0.0002	-58.26	0.00
γ_d	-0.0447	0.0389	-1.15	0.25	-0.0510	0.0332	-1.53	0.12	-0.0653	0.0369	-1.77	0.08
γ_{lp}	0.9002	0.5934	1.52	0.13	0.0400	0.3240	0.12	0.90	0.6856	0.3441	1.99	0.05
γ_{sp}	0.0055	0.0129	0.43	0.67	-0.0003	0.0111	-0.03	0.98	-0.0105	0.0127	-0.82	0.41
γ_{sd}	-0.0053	0.0119	-0.44	0.66	0.0005	0.0118	0.04	0.97	0.0163	0.0133	1.22	0.22
γ_{rs}	0.0016	0.0090	0.17	0.86	0.0066	0.0066	1.00	0.32	0.0055	0.0082	0.67	0.50
γ_{ps}	0.0029	0.0122	0.24	0.81	0.0204	0.0099	2.05	0.04	0.0205	0.0112	1.84	0.07
δ_{dd}	-0.4514	0.2592	-1.74	0.08	-0.3009	0.2152	-1.40	0.16	-1.0574	0.2628	-4.02	0.00
δ_{dlp}	0.3716	2.7542	0.13	0.89	-1.3675	1.0299	-1.33	0.18	-0.8496	1.2827	-0.66	0.51
δ_{dsp}	0.0242	0.0612	0.40	0.69	0.0352	0.0454	0.78	0.44	0.0138	0.0532	0.26	0.80
δ_{dsd}	-0.0458	0.0509	-0.90	0.37	-0.0442	0.0425	-1.04	0.30	-0.1061	0.0514	-2.06	0.04
δ_{drs}	0.0387	0.0367	1.06	0.29	0.0414	0.0278	1.49	0.14	0.0330	0.0347	0.95	0.34
δ_{dps}	-0.0607	0.0453	-1.34	0.18	-0.0137	0.0378	-0.36	0.72	-0.1229	0.0401	-3.07	0.00
λ_{dk}	0.0206	0.0037	5.62	0.00	0.0062	0.0035	1.79	0.07	0.0118	0.0047	2.50	0.01
λ_{dl}	0.0271	0.0077	3.51	0.00	-0.0029	0.0058	-0.50	0.62	0.0229	0.0072	3.18	0.00
λ_{de}	0.0013	0.0014	0.94	0.35	-0.0025	0.0010	-2.59	0.01	0.0007	0.0010	0.74	0.46
λ_{dm}	0.0349	0.0082	4.28	0.00	-0.0062	0.0062	-1.01	0.31	0.0166	0.0077	2.15	0.03

lower labor costs or a temporary surfeit of available workers at a time of declining national unemployment and a tightening labor market. In contrast, unemployment has a smaller and negative impact in 1992 and 2002, during periods of already high or rising unemployment. In those years, higher unemployment may instead signify regions experiencing more difficult times than the average. This explanation, however, does not apply in the same manner to the other two study industries. Higher unemployment rates are associated with substantially higher productivity in metalworking machinery in 1992 and 2002 but not in 1997, and with lower productivity in measuring and controlling device manufacturers in 1992 and 1997 but not in 2002. Regional unemployment

Table 7.4. Parameter Estimates for Rubber and Plastics (SIC 30), continued.

Year	1992				1997				2002			
Variable	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
λ_{lpk}	-0.0823	0.0717	-1.15	0.25	0.0253	0.0339	0.75	0.46	0.1586	0.0441	3.60	0.00
λ_{lpl}	0.0560	0.1522	0.37	0.71	-0.1051	0.0566	-1.86	0.06	0.0779	0.0674	1.16	0.25
λ_{lpe}	-0.0930	0.0279	-3.34	0.00	-0.0700	0.0093	-7.53	0.00	-0.0671	0.0095	-7.03	0.00
λ_{lpm}	0.0835	0.1653	0.50	0.61	0.1186	0.0620	1.91	0.06	0.3799	0.0730	5.21	0.00
λ_{spk}	0.0037	0.0015	2.41	0.02	0.0035	0.0014	2.48	0.01	0.0011	0.0020	0.57	0.57
λ_{spl}	-0.0001	0.0033	-0.04	0.97	0.0004	0.0023	0.15	0.88	-0.0016	0.0031	-0.51	0.61
λ_{spe}	0.0010	0.0006	1.60	0.11	-0.0002	0.0004	-0.42	0.67	0.0004	0.0004	0.91	0.36
λ_{spm}	0.0143	0.0035	4.13	0.00	0.0003	0.0026	0.12	0.90	0.0033	0.0033	0.99	0.32
λ_{sdk}	-0.0022	0.0013	-1.67	0.10	-0.0036	0.0015	-2.45	0.01	0.0008	0.0020	0.41	0.68
λ_{sdl}	0.0068	0.0028	2.40	0.02	0.0011	0.0024	0.44	0.66	0.0053	0.0030	1.73	0.08
λ_{sde}	0.0010	0.0005	1.92	0.06	0.0002	0.0004	0.57	0.57	-0.0004	0.0004	-1.04	0.30
λ_{sdm}	-0.0068	0.0030	-2.26	0.02	-0.0031	0.0026	-1.17	0.24	0.0030	0.0033	0.92	0.36
λ_{rsk}	-0.0006	0.0009	-0.69	0.49	0.0016	0.0008	2.04	0.04	0.0024	0.0012	2.03	0.04
λ_{rsl}	0.0028	0.0019	1.51	0.13	0.0033	0.0013	2.44	0.01	0.0032	0.0018	1.76	0.08
λ_{rse}	0.0012	0.0003	3.59	0.00	0.0017	0.0002	7.68	0.00	0.0016	0.0003	6.32	0.00
λ_{rsm}	-0.0073	0.0019	-3.80	0.00	0.0017	0.0014	1.17	0.24	-0.0013	0.0020	-0.67	0.50
λ_{psk}	0.0016	0.0013	1.24	0.22	-0.0028	0.0011	-2.48	0.01	0.0000	0.0015	-0.01	0.99
λ_{psl}	0.0073	0.0027	2.74	0.01	0.0076	0.0019	4.00	0.00	0.0109	0.0023	4.77	0.00
λ_{pse}	-0.0003	0.0005	-0.56	0.57	-0.0003	0.0003	-0.97	0.33	0.0007	0.0003	2.20	0.03
λ_{psm}	-0.0072	0.0029	-2.52	0.01	-0.0090	0.0021	-4.26	0.00	-0.0041	0.0025	-1.65	0.10
v_{de}	0.1412	0.0135	10.48	0.00	0.1488	0.0119	12.47	0.00	0.1917	0.0128	14.98	0.00
v_{se}	-0.1908	0.0096	-19.92	0.00	-0.1742	0.0088	-19.69	0.00	-0.1591	0.0102	-15.55	0.00
v_{cr1}	-0.0191	0.0145	-1.32	0.19	0.0181	0.0120	1.51	0.13	0.0011	0.0145	0.08	0.94
v_{cr2}	-0.0044	0.0131	-0.34	0.74	0.0030	0.0135	0.22	0.82	-0.0134	0.0156	-0.86	0.39
v_{cr3}	-0.0227	0.0172	-1.32	0.19	-0.0019	0.0145	-0.13	0.90	-0.0183	0.0196	-0.94	0.35
v_{pop}	0.0238	0.0082	2.91	0.00	0.0060	0.0068	0.87	0.38	0.0008	0.0083	0.10	0.92
v_{ue}	-0.4854	0.3069	-1.58	0.11	0.6835	0.2865	2.39	0.02	-0.2514	0.4870	-0.52	0.61
v_{inc}	0.1387	0.0508	2.73	0.01	0.0949	0.0430	2.21	0.03	0.0898	0.0460	1.95	0.05
v_{dv}	1.6090	1.1121	1.45	0.15	-1.4940	0.8522	-1.75	0.08	0.5539	0.8155	0.68	0.50
ρ_{dh}	-0.0119	0.0275	-0.43	0.67	-0.0020	0.0257	-0.08	0.94	-0.0595	0.0349	-1.71	0.09
ρ_{dvh}	-0.1477	0.9609	-0.15	0.88	-0.3487	0.5809	-0.60	0.55	0.7349	0.6548	1.12	0.26
Generalized R^2			0.9992				0.9995				0.9990	
Equation Adjusted R^2												
Production Function			0.9569				0.9630				0.9485	
Capital Cost Share			0.7785				0.7963				0.7807	
Labor Cost Share			0.7506				0.7646				0.6964	
Materials Cost Share			0.8753				0.8842				0.8577	

appears to be industry-specific in its association with establishment-level productivity outcomes.

The measure of industrial diversity is inverted, so that negative coefficients indicate a productivity benefit to being located in a more industrially diverse region. The estimated coefficients are large and negative in the measuring and controlling devices

Table 7.5. Parameter Estimates for Metalworking Machinery (SIC 354).

Year	1992				1997				2002			
Variable	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
α_0	7.1519	0.0144	497.15	0.00	7.3822	0.0163	453.86	0.00	7.5604	0.0167	451.89	0.00
α_k	0.0855	0.0006	152.77	0.00	0.1239	0.0007	174.73	0.00	0.1354	0.0010	134.41	0.00
α_l	0.5615	0.0031	179.99	0.00	0.5197	0.0025	208.85	0.00	0.5048	0.0034	149.88	0.00
α_e	0.0161	0.0002	104.29	0.00	0.0138	0.0001	94.75	0.00	0.0128	0.0002	79.87	0.00
α_m	0.3080	0.0017	177.82	0.00	0.3004	0.0015	204.72	0.00	0.2936	0.0020	148.85	0.00
β_{kk}	0.0635	0.0006	109.09	0.00	0.0805	0.0007	112.13	0.00	0.0803	0.0009	90.96	0.00
β_{ll}	0.1827	0.0023	78.69	0.00	0.1749	0.0021	81.96	0.00	0.1413	0.0024	57.79	0.00
β_{ee}	0.0131	0.0002	63.41	0.00	0.0131	0.0002	66.07	0.00	0.0112	0.0002	59.24	0.00
β_{mm}	0.1701	0.0012	141.10	0.00	0.1739	0.0011	157.19	0.00	0.1540	0.0013	116.10	0.00
β_{kl}	-0.0379	0.0007	-54.58	0.00	-0.0458	0.0009	-53.85	0.00	-0.0474	0.0010	-47.01	0.00
β_{ke}	-0.0009	0.0002	-4.88	0.00	-0.0013	0.0002	-6.91	0.00	-0.0012	0.0002	-6.64	0.00
β_{km}	-0.0286	0.0004	-64.30	0.00	-0.0379	0.0005	-72.50	0.00	-0.0400	0.0006	-62.21	0.00
β_{le}	-0.0059	0.0003	-21.65	0.00	-0.0060	0.0003	-21.97	0.00	-0.0048	0.0003	-17.58	0.00
β_{lm}	-0.1400	0.0014	-96.83	0.00	-0.1313	0.0012	-108.05	0.00	-0.1194	0.0015	-81.48	0.00
β_{em}	-0.0061	0.0002	-31.82	0.00	-0.0060	0.0002	-32.91	0.00	-0.0056	0.0002	-31.33	0.00
γ_d	-0.0875	0.0413	-2.12	0.03	-0.2001	0.0407	-4.91	0.00	-0.1900	0.0518	-3.67	0.00
γ_{lp}	-0.5118	0.9727	-0.53	0.60	-2.8258	0.9361	-3.02	0.00	0.0596	0.6300	0.09	0.92
γ_{sp}	0.0245	0.0171	1.43	0.15	0.0303	0.0176	1.72	0.09	-0.0404	0.0181	-2.23	0.03
γ_{sd}	-0.0116	0.0128	-0.91	0.36	-0.0458	0.0158	-2.89	0.00	0.0252	0.0170	1.48	0.14
γ_{rs}	-0.0288	0.0097	-2.97	0.00	0.0049	0.0106	0.46	0.65	-0.0194	0.0111	-1.76	0.08
γ_{ps}	0.0760	0.0168	4.53	0.00	0.0832	0.0146	5.72	0.00	0.1058	0.0175	6.05	0.00
δ_{dd}	0.2874	0.2866	1.00	0.32	0.8210	0.2773	2.96	0.00	-0.0518	0.3284	-0.16	0.87
δ_{dlp}	-1.3681	4.7337	-0.29	0.77	-2.7493	3.2652	-0.84	0.40	0.8008	2.5847	0.31	0.76
δ_{dsp}	-0.0953	0.0798	-1.19	0.23	0.0227	0.0846	0.27	0.79	-0.0993	0.0836	-1.19	0.24
δ_{dsd}	0.0513	0.0497	1.03	0.30	0.0410	0.0600	0.68	0.49	0.1315	0.0729	1.80	0.07
δ_{drs}	0.0128	0.0371	0.34	0.73	-0.0402	0.0368	-1.09	0.27	-0.0178	0.0437	-0.41	0.68
δ_{dps}	0.0349	0.0760	0.46	0.65	0.0289	0.0574	0.50	0.62	-0.1208	0.0677	-1.78	0.07
λ_{dk}	0.0040	0.0026	1.51	0.13	0.0080	0.0034	2.34	0.02	0.0193	0.0045	4.28	0.00
λ_{dl}	-0.0252	0.0114	-2.21	0.03	-0.0302	0.0096	-3.14	0.00	-0.0003	0.0123	-0.02	0.98
λ_{de}	-0.0015	0.0009	-1.65	0.10	0.0010	0.0009	1.12	0.26	0.0008	0.0010	0.81	0.42
λ_{dm}	0.0226	0.0070	3.21	0.00	0.0285	0.0061	4.63	0.00	0.0314	0.0081	3.85	0.00

industry, and are substantial for metalworking machinery establishments as well, suggesting Jacobs externality benefits arising from cross-industry knowledge or technology spillovers. The rubber and plastics models show mixed results, with productivity positively associated with industrial diversity in 1997 but instead paired with lesser levels of industrial diversity in 1992 and 2002. The contrast between the measuring and controlling devices and rubber and plastics industries is consistent with an industry lifecycle interpretation that holds that whereas more technology- and innovation-intensive industries benefit from local diversity of thought and spillovers across industry sectors, more traditional manufacturing sectors may instead profit from having local

Table 7.5. Parameter Estimates for Metalworking Machinery (SIC 354), continued.

Year	1992				1997				2002			
Variable	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
λ_{lpk}	-0.0502	0.0680	-0.74	0.46	-0.0719	0.0762	-0.94	0.35	0.0476	0.0610	0.78	0.44
λ_{lpl}	0.4071	0.2908	1.40	0.16	0.1668	0.2172	0.77	0.44	0.5938	0.1700	3.49	0.00
λ_{lpe}	0.0553	0.0233	2.37	0.02	-0.0660	0.0193	-3.41	0.00	-0.0627	0.0128	-4.90	0.00
λ_{lpm}	-0.0204	0.1809	-0.11	0.91	0.0397	0.1366	0.29	0.77	0.1275	0.1079	1.18	0.24
λ_{spk}	0.0031	0.0011	2.67	0.01	0.0006	0.0019	0.32	0.75	-0.0008	0.0021	-0.38	0.70
λ_{spl}	0.0082	0.0049	1.66	0.10	0.0044	0.0054	0.83	0.41	-0.0149	0.0060	-2.49	0.01
λ_{spe}	-0.0010	0.0004	-2.52	0.01	0.0005	0.0005	0.94	0.35	0.0003	0.0005	0.65	0.52
λ_{spm}	0.0099	0.0030	3.23	0.00	-0.0010	0.0034	-0.29	0.77	-0.0045	0.0038	-1.18	0.24
λ_{sdk}	-0.0020	0.0008	-2.61	0.01	-0.0023	0.0015	-1.56	0.12	0.0030	0.0017	1.74	0.08
λ_{sdl}	-0.0056	0.0033	-1.72	0.08	0.0024	0.0042	0.57	0.57	0.0228	0.0048	4.71	0.00
λ_{sde}	0.0012	0.0003	4.58	0.00	0.0001	0.0004	0.22	0.82	-0.0004	0.0004	-1.03	0.30
λ_{sdm}	-0.0063	0.0020	-3.15	0.00	-0.0005	0.0027	-0.19	0.85	0.0104	0.0030	3.45	0.00
λ_{rsk}	0.0003	0.0006	0.47	0.64	0.0006	0.0009	0.63	0.53	-0.0023	0.0012	-1.96	0.05
λ_{rsl}	0.0049	0.0027	1.78	0.08	-0.0103	0.0025	-4.05	0.00	-0.0098	0.0032	-3.05	0.00
λ_{rse}	0.0014	0.0002	6.65	0.00	0.0015	0.0002	6.42	0.00	0.0011	0.0002	4.39	0.00
λ_{rsm}	0.0015	0.0017	0.87	0.38	0.0018	0.0016	1.11	0.27	-0.0042	0.0021	-2.00	0.05
λ_{psk}	-0.0011	0.0012	-0.94	0.35	0.0028	0.0014	1.94	0.05	0.0009	0.0018	0.53	0.60
λ_{psl}	0.0017	0.0051	0.33	0.74	0.0036	0.0040	0.88	0.38	0.0120	0.0049	2.46	0.01
λ_{pse}	0.0008	0.0004	1.97	0.05	0.0014	0.0004	3.98	0.00	0.0005	0.0004	1.42	0.16
λ_{psm}	-0.0037	0.0032	-1.16	0.25	0.0048	0.0026	1.87	0.06	0.0002	0.0031	0.05	0.96
v_{de}	0.1779	0.0174	10.24	0.00	0.2099	0.0156	13.42	0.00	0.2165	0.0184	11.80	0.00
v_{se}	-0.1732	0.0113	-15.32	0.00	-0.1249	0.0105	-11.87	0.00	-0.1583	0.0137	-11.60	0.00
v_{cr1}	-0.0248	0.0222	-1.11	0.26	0.0774	0.0228	3.40	0.00	-0.0139	0.0276	-0.51	0.61
v_{cr2}	0.0145	0.0158	0.92	0.36	0.0665	0.0193	3.45	0.00	0.0345	0.0200	1.72	0.09
v_{cr3}	-0.0848	0.0250	-3.39	0.00	0.0069	0.0227	0.30	0.76	-0.0969	0.0307	-3.16	0.00
v_{pop}	0.0359	0.0093	3.85	0.00	0.0156	0.0084	1.87	0.06	0.0215	0.0121	1.77	0.08
v_{ue}	0.5893	0.3471	1.70	0.09	-0.1135	0.6295	-0.18	0.86	2.1589	0.7531	2.87	0.00
v_{inc}	-0.0238	0.0752	-0.32	0.75	-0.1051	0.0722	-1.46	0.15	-0.1869	0.0829	-2.26	0.02
v_{dv}	-3.1462	1.3903	-2.26	0.02	-4.0410	1.3425	-3.01	0.00	-4.0307	1.2933	-3.12	0.00
ρ_{dh}	-0.0179	0.0367	-0.49	0.63	-0.0143	0.0357	-0.40	0.69	0.2221	0.0425	5.23	0.00
ρ_{dvh}	0.5574	1.0236	0.54	0.59	-0.9196	0.7557	-1.22	0.22	-0.4974	1.0646	-0.47	0.64
Generalized R^2			0.9989				0.9991				0.9986	
Equation Adjusted R^2												
Production Function			0.9420				0.9517				0.9351	
Capital Cost Share			0.7612				0.7576				0.7535	
Labor Cost Share			0.7445				0.7388				0.7367	
Materials Cost Share			0.8512				0.8784				0.8576	

resources targeted more specifically to a restricted set of regional industrial strengths. (The metalworking machinery industry, however, does not fit the profile as a technology-intensive industry.) It should be noted that the effects of industrial diversity are small despite the sizeable coefficient values: the Herfindahl-Hirschman index measuring industrial diversity has mean values ranging from 0.013 to 0.015 across the nine samples and correspondingly small standard deviations (see Table 6.4). Even in the model

Table 7.6. Parameter Estimates for Measuring and Controlling Devices (SIC 382).

Year	1992				1997				2002			
Variable	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
α_0	8.2787	0.0270	306.14	0.00	8.4910	0.0269	315.55	0.00	8.7729	0.0478	183.58	0.00
α_k	0.0935	0.0014	68.31	0.00	0.1222	0.0016	78.34	0.00	0.1280	0.0021	61.57	0.00
α_l	0.4313	0.0055	78.83	0.00	0.3983	0.0046	86.53	0.00	0.3958	0.0057	69.51	0.00
α_e	0.0105	0.0002	45.58	0.00	0.0093	0.0002	37.35	0.00	0.0075	0.0002	42.99	0.00
α_m	0.3737	0.0047	79.87	0.00	0.3772	0.0043	88.41	0.00	0.3670	0.0052	70.77	0.00
β_{kk}	0.0720	0.0013	54.65	0.00	0.0731	0.0013	55.54	0.00	0.0649	0.0015	42.26	0.00
β_{ll}	0.1354	0.0039	35.10	0.00	0.1208	0.0035	34.70	0.00	0.1208	0.0040	30.20	0.00
β_{ee}	0.0083	0.0003	30.45	0.00	0.0091	0.0003	30.26	0.00	0.0064	0.0002	31.78	0.00
β_{mm}	0.1458	0.0026	55.62	0.00	0.1583	0.0025	63.09	0.00	0.1451	0.0029	49.70	0.00
β_{kl}	-0.0356	0.0014	-25.22	0.00	-0.0258	0.0014	-18.25	0.00	-0.0264	0.0017	-15.71	0.00
β_{ke}	-0.0002	0.0003	-0.79	0.43	-0.0020	0.0003	-6.89	0.00	-0.0008	0.0002	-4.70	0.00
β_{km}	-0.0397	0.0011	-36.80	0.00	-0.0485	0.0011	-43.07	0.00	-0.0431	0.0014	-31.35	0.00
β_{le}	-0.0031	0.0004	-8.53	0.00	-0.0016	0.0004	-3.66	0.00	-0.0019	0.0002	-7.57	0.00
β_{lm}	-0.1080	0.0027	-40.68	0.00	-0.1075	0.0023	-45.78	0.00	-0.1049	0.0028	-37.01	0.00
β_{em}	-0.0051	0.0003	-17.62	0.00	-0.0053	0.0003	-16.56	0.00	-0.0037	0.0002	-19.23	0.00
γ_d	-0.3532	0.1832	-1.93	0.05	-0.2499	0.1441	-1.73	0.08	0.1184	0.1793	0.66	0.51
γ_{lp}	1.3261	0.8434	1.57	0.12	0.3648	0.6146	0.59	0.55	-0.2681	0.8890	-0.30	0.76
γ_{sp}	-0.0222	0.0265	-0.84	0.40	0.0285	0.0189	1.51	0.13	-0.0036	0.0224	-0.16	0.87
γ_{sd}	0.0029	0.0227	0.13	0.90	-0.0173	0.0184	-0.95	0.34	-0.0166	0.0238	-0.70	0.48
γ_{rs}	0.0238	0.0118	2.01	0.04	0.0174	0.0103	1.69	0.09	0.0111	0.0131	0.84	0.40
γ_{ps}	0.0907	0.0443	2.05	0.04	0.0820	0.0393	2.09	0.04	0.0607	0.0421	1.44	0.15
δ_{dd}	1.2189	0.9506	1.28	0.20	2.7059	1.2170	2.22	0.03	-3.0457	1.7200	-1.77	0.08
δ_{dlp}	7.8619	4.0158	1.96	0.05	-3.2199	3.8251	-0.84	0.40	-6.7057	5.8258	-1.15	0.25
δ_{dsp}	-0.1091	0.1404	-0.78	0.44	0.1146	0.1183	0.97	0.33	-0.3717	0.1824	-2.04	0.04
δ_{dsd}	0.0706	0.1074	0.66	0.51	-0.1726	0.1092	-1.58	0.11	0.1565	0.1318	1.19	0.24
δ_{drs}	-0.0127	0.0532	-0.24	0.81	0.0575	0.0624	0.92	0.36	-0.1388	0.0760	-1.83	0.07
δ_{dps}	0.0251	0.2747	0.09	0.93	0.1176	0.2618	0.45	0.65	0.6262	0.3055	2.05	0.04
λ_{dk}	0.0074	0.0067	1.11	0.27	-0.0029	0.0085	-0.33	0.74	-0.0053	0.0116	-0.45	0.65
λ_{dl}	0.0640	0.0215	2.98	0.00	0.0349	0.0213	1.64	0.10	0.0236	0.0273	0.86	0.39
λ_{de}	-0.0039	0.0015	-2.68	0.01	-0.0055	0.0019	-2.88	0.00	-0.0021	0.0012	-1.75	0.08
λ_{dm}	0.0360	0.0179	2.01	0.04	0.0235	0.0190	1.24	0.22	-0.0037	0.0240	-0.15	0.88

boasting the largest industrial diversity coefficient, measuring and controlling devices in 1992, an drop in industrial diversity of an entire standard deviation from the sample mean is associated with a decline of only about four percent in output. The effects of historic diversity, i.e., the change in the industrial diversity measure from the historical period to the sample year, are negligible and never rise to conventional levels of significance. In alternative models omitting the historic diversity variable, the estimated coefficients for current-period industrial diversity remain nearly the same, verifying that the effect of industrial diversity is current and does not depend on the relationship with past industrial diversity.

Table 7.6. Parameter Estimates for Measuring and Controlling Devices (SIC 382), continued.

Year	1992				1997				2002			
Variable	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
λ_{lpk}	-0.5054	0.0666	-7.59	0.00	-0.0970	0.0587	-1.65	0.10	0.1686	0.0870	1.94	0.05
λ_{lpl}	-1.3694	0.2119	-6.46	0.00	0.0100	0.1486	0.07	0.95	0.3340	0.1988	1.68	0.09
λ_{lpe}	-0.0015	0.0142	-0.11	0.91	-0.0112	0.0129	-0.87	0.38	-0.0253	0.0091	-2.78	0.01
λ_{lpm}	-1.3705	0.1801	-7.61	0.00	-0.4166	0.1340	-3.11	0.00	-0.0436	0.1757	-0.25	0.80
λ_{spk}	0.0096	0.0020	4.88	0.00	0.0030	0.0018	1.65	0.10	0.0032	0.0025	1.27	0.20
λ_{spl}	0.0283	0.0063	4.48	0.00	0.0045	0.0046	0.98	0.33	0.0040	0.0058	0.69	0.49
λ_{spe}	0.0013	0.0004	3.08	0.00	0.0002	0.0004	0.39	0.70	0.0011	0.0003	4.15	0.00
λ_{spm}	0.0295	0.0054	5.48	0.00	0.0057	0.0041	1.38	0.17	0.0101	0.0052	1.94	0.05
λ_{sdk}	-0.0053	0.0016	-3.21	0.00	-0.0028	0.0017	-1.60	0.11	-0.0043	0.0024	-1.76	0.08
λ_{sdl}	-0.0160	0.0052	-3.05	0.00	-0.0006	0.0043	-0.14	0.89	-0.0013	0.0057	-0.23	0.82
λ_{sde}	-0.0006	0.0004	-1.83	0.07	0.0001	0.0004	0.23	0.82	-0.0009	0.0003	-3.59	0.00
λ_{sdm}	-0.0190	0.0045	-4.19	0.00	-0.0046	0.0038	-1.20	0.23	-0.0139	0.0052	-2.69	0.01
λ_{rsk}	-0.0006	0.0010	-0.62	0.54	-0.0015	0.0011	-1.37	0.17	0.0009	0.0013	0.71	0.48
λ_{rsl}	0.0129	0.0032	3.98	0.00	0.0086	0.0027	3.15	0.00	0.0048	0.0031	1.56	0.12
λ_{rse}	-0.0002	0.0002	-0.92	0.36	-0.0002	0.0002	-0.84	0.40	0.0004	0.0001	3.09	0.00
λ_{rsm}	0.0032	0.0027	1.19	0.23	-0.0022	0.0024	-0.90	0.37	0.0010	0.0028	0.38	0.71
λ_{psk}	0.0002	0.0034	0.05	0.96	-0.0009	0.0034	-0.27	0.79	0.0042	0.0040	1.05	0.29
λ_{psl}	0.0271	0.0110	2.46	0.01	0.0169	0.0085	1.99	0.05	0.0281	0.0093	3.04	0.00
λ_{pse}	-0.0009	0.0007	-1.23	0.22	0.0013	0.0007	1.82	0.07	0.0005	0.0004	1.10	0.27
λ_{psm}	-0.0033	0.0091	-0.36	0.72	0.0023	0.0074	0.30	0.76	-0.0022	0.0081	-0.28	0.78
v_{de}	0.2313	0.0351	6.58	0.00	0.2507	0.0318	7.88	0.00	0.2750	0.0356	7.72	0.00
v_{se}	-0.2715	0.0286	-9.51	0.00	-0.2542	0.0264	-9.63	0.00	-0.2216	0.0315	-7.04	0.00
v_{cr1}	0.0188	0.0373	0.51	0.61	-0.0078	0.0324	-0.24	0.81	-0.0892	0.0514	-1.73	0.08
v_{cr2}	-0.0066	0.0395	-0.17	0.87	-0.0243	0.0393	-0.62	0.54	-0.1172	0.0428	-2.74	0.01
v_{cr3}	0.0150	0.0331	0.45	0.65	0.0769	0.0309	2.48	0.01	-0.0804	0.0533	-1.51	0.13
v_{pop}	-0.0132	0.0321	-0.41	0.68	0.0486	0.0214	2.27	0.02	0.0765	0.0271	2.82	0.00
v_{ue}	-0.8074	1.3198	-0.61	0.54	-2.8199	1.3475	-2.09	0.04	1.5269	2.0725	0.74	0.46
v_{inc}	-0.3069	0.1365	-2.25	0.02	-0.0912	0.1289	-0.71	0.48	-0.0915	0.1583	-0.58	0.56
v_{dv}	-22.1439	7.8192	-2.83	0.00	-9.5446	5.6585	-1.69	0.09	-5.8544	8.8070	-0.66	0.51
ρ_{dh}	-0.0642	0.1100	-0.58	0.56	0.1107	0.0863	1.28	0.20	0.0283	0.1033	0.27	0.78
ρ_{dvh}	1.1099	6.5078	0.17	0.86	3.9798	3.7599	1.06	0.29	-4.1376	6.5063	-0.64	0.52
Generalized R^2			0.9983				0.9984				0.9975	
Equation Adjusted R^2												
Production Function			0.9409				0.9455				0.9372	
Capital Cost Share			0.7461				0.7629				0.6756	
Labor Cost Share			0.6553				0.6463				0.6209	
Materials Cost Share			0.8026				0.8371				0.7896	

Population density, introduced into the model partly to help control for regional size effects such as absolute levels of resources and agglomeration economies, demonstrates consistently positive effects on productivity, suggesting that urban economies outweigh congestion and other diseconomies of density. The magnitude of the influence is quite small in practical terms. It would require an increase in population density of more than 13 percent to increase average output by one percent for measuring and controlling devices plants in 2002. The analogous figure is larger for the other sample industry-years that exhibit smaller estimated coefficients of population density.

The three Census Region dummies evidence a surprising degree of variation over time. The Midwest is the most productive area of the nation for metalworking machinery establishments in 1992 and again in 2002, though it is slightly surpassed by the South in 1997. The differences between the Census Regions are substantial: establishments in the West are eight percent less productive in 1992, Midwestern and Southern plants are six to eight percent more productive in 1997, and Western metalworking machinery plants are nearly ten percent less productive in 2002 than the average Northeastern establishment. There are large contrasts in the measuring and controlling devices sector as well, with the West the most productive area in 1997 and the Northeast in 2002. Shifts in military contracting may play an considerable role in creating these patterns. In the rubber and plastics industry, none of the coefficients are significant at the 90 percent level or more, and the productivity ordering of the Census Regions shifts by study year, but still there is as much as a two percent difference in average output across regions. Although the patterns of relative productivity across Census Regions change more than expected, perhaps it is an indication that the dummies are indeed capturing macro-regional differences in economic conditions that are not apparent in examining the three industries at the national scale.

7.3.4. Regional Industrial Dominance

With regional industrial dominance the concept at the heart of this research, the most striking and important result reported in the estimations in Tables 7.4 through 7.6 is that regional industrial dominance is an influential negative factor in determining establishment-level productivity. In the metalworking machinery manufacturing industry, all else equal, a rise of 20 percent in the total industry shipment value accounted for by the top five firms in an LMA in 1992 is associated with a two percent decline in output at the sample means.[87] The figure grows to approximately four percent in 1997 and 2002. The effect is even greater for measuring and controlling device manufacturers: a hike of 20 percent in the concentration ratio yields a seven percent dropoff in production in the 1992 sample and a five percent drop in 1997. The estimated coefficient of dominance is positive but not significant in 2002. The rubber and plastics industry evidences smaller but substantial effects from regional industrial dominance: declines of about 1.0 to 1.3 percent in output associated with a 20 percent rise in the concentration ratio. These observations provide the start of an answer to the first research question driving this study: other things being equal, manufacturing plants are less productive in regions where the industry is locally dominated.

As far as the author is aware, there is only one previous empirical result that can be used for comparison. The coefficient of regional industrial dominance calculated here for the 1992 measuring and controlling devices model is roughly three times larger than the estimated effect of a four-firm manufacturing-wide concentration ratio reported by Feser (2002) for the same industry and year but across a somewhat different sample. Feser's study does not include dummy variables for plant dominance status and does not examine nonlinearities or interactions in the effects of dominance.

[87] Note that since the dominance variable is a ratio by construction, it is not transformed by natural logarithm to enter the production function. The estimated coefficient is interpreted as the percent change in output associated with a rise in the concentration ratio of 100 percent from the sample mean. The figure of 20 percent used as an illustration represents approximately one standard deviation of the concentration ratio dominance measure in the estimation samples (see Table 6.3).

It is important to make clear that because the production function specification includes dummy variables that indicate relatively large and small firms in a regional industry, the estimated coefficients of the regional industrial dominance measure do not simply reflect dominating companies outperforming locally dominated enterprises. Rather, regional industrial dominance influences the productivity of plants in the three study industries independently of their status as part of a dominator or a dominated firm.[88] The dummy terms indicate that in all nine of the industry-year samples, establishments belonging to dominator firms outperform, and dominated firms underperform, the sample averages. The margins by which this occurs are very substantial: dominators enjoy a 14 to 19 percent productivity advantage in rubber and plastics manufacturing, 18 to 22 percent in metalworking machinery, and 23 to 28 percent in measuring and controlling devices. Dominated plants suffer a production deficit below the industry averages of similar magnitude. In each model, these dummy variables are among the most significant regressors, and whether a plant belongs to a dominator firm, a dominated firm, or neither is the strongest single influence on output other than input quantities. These impacts—both the direction and the scale—are to be expected. Dominator firms have more resources at their disposal and generally can take advantage of economies of scale, whereas dominated firms have access to fewer resources and economies of scale than the average industry establishment. In the cross-sectional modeling context, the causal direction of the effects indicated by the dummy variables is ambiguous; dominant firms may have achieved their relative size due to

[88] Interactions between dominance and the dominance classification dummies tested in alternative specifications are inconsistent and insignificant. Either regional industrial dominance affects plants of all types equally or, more likely, the regression does not possess sufficient statistical power to distinguish among dominance productivity effects according to establishment dominance status.

unobserved firm-specific efficiencies.

The figures in the preceding paragraphs are direct effects, equivalent to the marginal effects of dominance evaluated at the sample means of all the variables. For variables that enter the production function nonlinearly, the estimated marginal effects vary according to where in the sample space they are evaluated. Regional industrial dominance enters in quadratic form and is interacted in the production function with both the standard input and agglomeration economy variables. Therefore, the estimated marginal effects of dominance vary with the levels of inputs and potential agglomeration economies and with the base level of dominance. The nonlinearities modeled via interactions in this way are simple, just an increasing or decreasing trend in relation to the interacted variable (Aiken and West 1991).[89] (Although it is possible to calculate the marginal effect of dominance at any point within or even external to the sample set, the sheer volume of possibilities makes such an exploration intractable.)

The degree to which changes in regional industrial dominance are associated with modifications in the levels of production depends on the level of dominance itself. For the rubber and plastics industry, and in 2002 for the measuring and controlling devices industry, the estimated coefficient of the square of dominance is large and negative, so that the negative impact of dominance on performance increases as the level of dominance rises. The opposite, however, is true in 1992 and 1997 for the metalworking machinery and the measuring and controlling devices industries: a positive dominance-squared term indicates that the deleterious effects of dominance on production are felt

[89] Given the number of variables included in this translog production function model, more complex specifications would quickly surpass the statistical power of the estimation procedure.

most acutely in those regions with moderate levels of industrial dominance.[90] Figure 7.1 illustrates the estimated marginal effects of dominance in each model accounting for both the linear and squared terms.

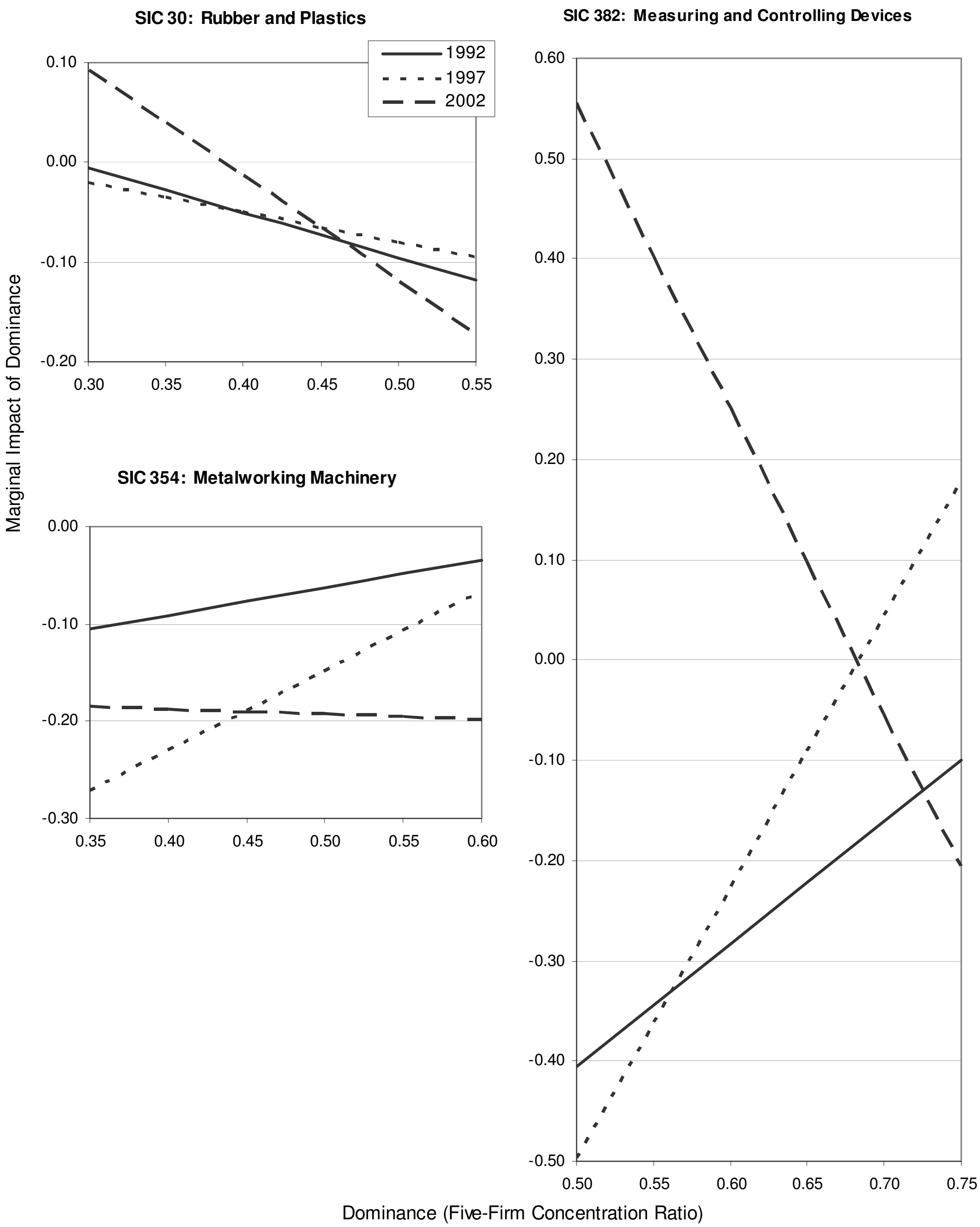
The influence of dominance on establishment-level productivity also changes with the levels of standard inputs and agglomeration economies. These nonlinearities are highly relevant to understanding the effects of regional industrial dominance in a manner useful for policymaking, since potential agglomeration economies vary widely across regions and the quantities of standard inputs are a useful proxy for establishment size. Again, since it is not feasible to examine the effects of dominance at all combinations of agglomeration economies and inputs, the scope of the analysis is restrained to contrasting regions with less than average potential agglomeration economies with better endowed LMAs, and considering the range of plant sizes as indicated by the volume of inputs. Also, it is worth reiterating that the point of estimation is at the sample means, and that interpretations are less reliable moving further away from the means.[91] Therefore, the variation in the effects of regional industrial dominance according to the levels of interacted model variables is interpreted qualitatively, emphasizing broad trends rather than specific results. The following paragraphs investigate the interaction between dominance and input levels; the interaction between dominance and agglomeration is considered in section 7.4.6.

Examined individually, the interaction terms between dominance and the standard

[90] At low levels of dominance, the impact on production is small because there is very little dominance. At high levels of dominance, the negative contribution to production represented by the linear dominance term is balanced by the positive quadratic term.

[91] This is reflected in part by the increasing width of the confidence intervals moving away from the means in Figures 7.2 and 7.3.

Figure 7.1. Marginal Impacts of Regional Industrial Dominance by Level of Dominance.

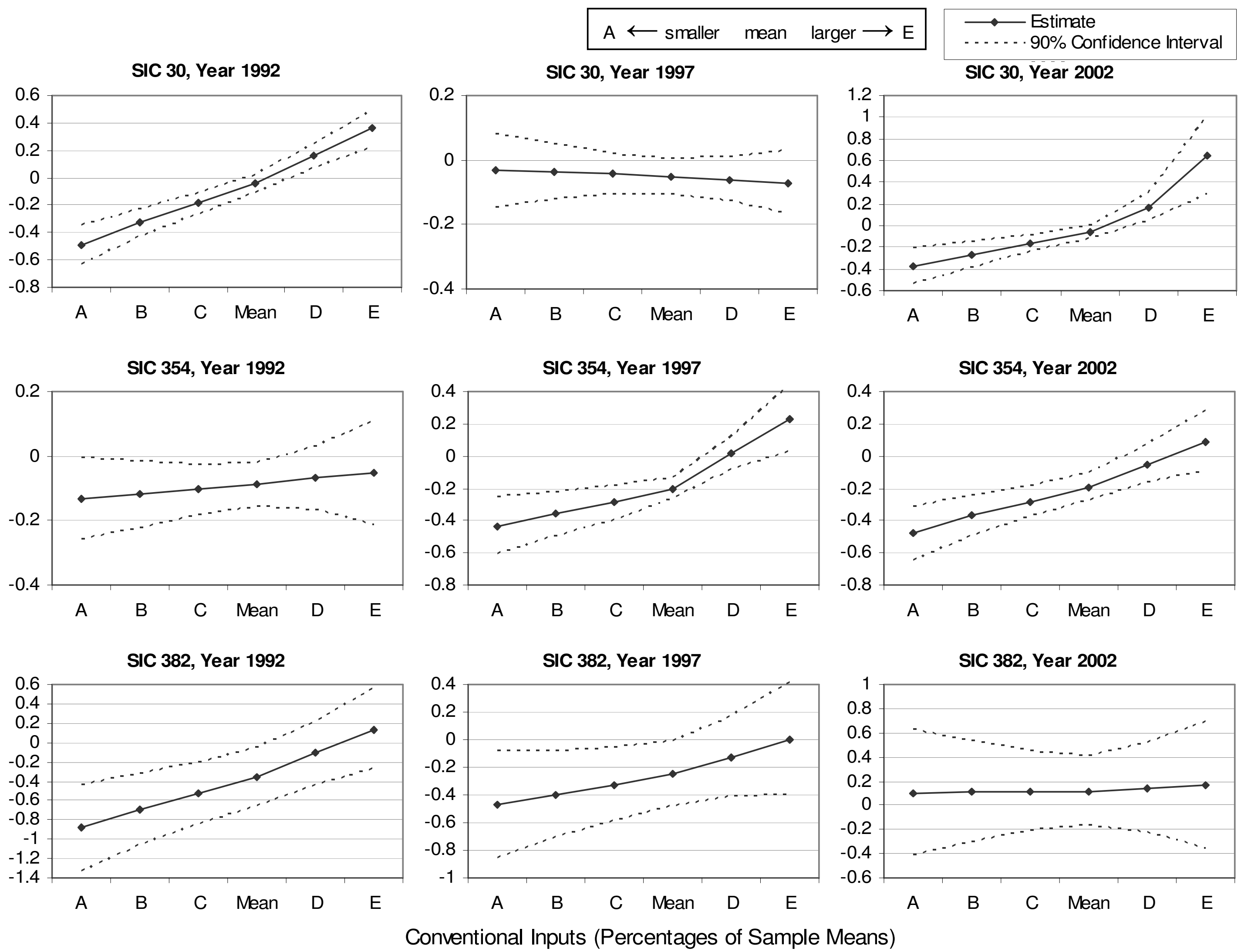


inputs reveal that dominance is labor-augmenting for measuring and controlling devices, is materials-augmenting in metalworking machinery, and tends to lead to greater use of all four factor inputs in the rubber and plastics industry. The manner in which the effects of dominance on production adjust as the levels of the inputs change together—a proxy for plant size—is more interesting (Braumoeller 2004; Brambor and Clark 2006). Figure 7.2 displays the estimates of the marginal impacts of regional industrial dominance on output and their 90 percent confidence intervals for different amounts of standard inputs. The graphs require some explanation. The vertical axes represent the estimated marginal impact of dominance, interpreted in the same way as the estimated coefficients of dominance reported in Tables 7.4 through 7.6 and the vertical axes in Figure 7.1: the percent change in output associated with a rise in the concentration ratio of 100 percent from the sample mean, with all other variables held constant. The horizontal axes provide six points that describe the range from low to high quantities of the four standard inputs. The point labeled "mean" is defined by the sample mean values for the four standard inputs: capital, labor, energy, and materials. The disclosure restrictions that protect the confidentiality of data pertaining to individual establishments preclude the use of percentiles to populate the rest of the input range. Instead, the five points labeled "A" through "E" are constructed as percentages of the sample means. A, B, and C are smaller than the mean and D and E are larger than the mean. At each of these points, the sample means for capital, labor, energy, and materials are multiplied by selected fractions and the estimated marginal impact of regional dominance is calculated for the resulting input quantities. The five fractions for points A through E are chosen separately for each of the four inputs in each of the nine samples to approximate the range observed for that industry and year. For example, point B for rubber and plastics (SIC 30) in 1992 refers to 50 percent of the sample mean for capital, 40 percent for labor, 60 percent for energy, and 50 percent for materials.[92] The purpose of this procedure is to ensure that the points along the horizontal axes that together approximate the range of standard inputs represent hypothetical combinations of inputs rather than actual sample observations and thus uphold confidentiality requirements. Note that the horizontal axes are not to scale; the six points are not necessarily equally spaced along the continuum from low to high input quantities.

As described earlier, the effects of regional industrial dominance at the sample means in the rubber and plastics industry are small but negative. From Figure 7.2, it is evident that in the 1997 model, as plant size shifts away from the mean amounts of the four standard inputs, the effect of dominance changes only slowly and the significance of the estimated coefficients decreases (the confidence intervals widen and include zero). In the 1992 and 2002 models, however, small plants experience greater and more significant negative effects of dominance. In other words, dominance acts as more of a hindrance to productivity performance for the lower throughput, smaller rubber and plastics plants in 1992 and in 2002. The largest establishments instead benefit from industrial dominance in their regions. Scanning the other graphs in Figure 7.2, the latter pattern is replicated in most of the rest of the models: the estimated marginal effect of dominance is greater in magnitude (a larger negative number) and more significant for smaller plants. Only the 2002 measuring and controlling devices (SIC 382) and the 1992 metalworking machinery (SIC 354) models display a result more like that for rubber and plastics in 1997, wherein the effect of dominance is stable across establishment sizes. Industry-specific conditions

[92] The precise fractions for each input, industry, and year are available from the author.

Figure 7.2. Marginal Impacts of Regional Industrial Dominance Across Range of Standard Inputs.



in these particular years may have favored the smaller firms in dominated regional industries.

The influence of dominance on establishment productivity appears to be primarily a current phenomenon. The estimated coefficients of the historic dominance term are mostly insignificant and quite small, particularly in comparison to the magnitude of the typical change in the concentration ratio measure of dominance over the twenty-year period.[93] Only the 2002 models for metalworking machinery and for rubber and plastics demonstrate significant impacts from the change in dominance. For the metalworking machinery plants, the positive coefficient indicates that an increase in measured dominance (i.e., a low historical level of dominance) boosts productivity, but in the rubber and plastics industry the effect is in the opposite direction. Omitting the historic dominance variable entirely leaves the current dominance coefficients about the same, so that as with industrial diversity it is possible to conclude that the predominant effects are current and do not depend on past levels of dominance. The minimal influence of historic as opposed to current dominance is certainly reasonable given the changes in industry composition, products and production technologies, and national economic conditions over the intervening period.

7.3.5. Agglomeration Economies

Although the results for regional industrial dominance are strong and largely consistent across industries and years, the same does not hold true for agglomeration economies. As noted in Chapter Six, labor pooling advantages might be expected to be

[93] Note that the change in dominance is not displayed in Table 6.4 (instead the table contains descriptive statistics for the *level* of dominance twenty years prior).

the most important in the measuring and controlling devices industry and least important to plants in the rubber and plastics industry, judging from the industries' relative reliance on labor inputs. In fact, the benefits of potential regional labor pools on production seem to vary across the sample years for each industry. Labor pools confer productivity advantages for measuring and controlling devices in the 1992 model, such that a two percent rise in the distance-weighted fraction of the local workforce employed in the top 15 occupations is associated with a 2.7 percent increase in output.[94] That figure drops to less than one percent in 1997 and becomes negative in 2002, perhaps reflecting the industry becoming more capital-intensive. Two of the three sample years show negative impacts from labor pooling for metalworking machinery establishments. Rubber and plastics plants do benefit from potential labor pools in 1992 and 2002, but in 1997 the effect is negligible. As the only one of the agglomeration economies to be measured by a relative rather than an absolute indicator, some of benefits that arise due to the size of the suitable local labor force may be captured in the model by the other size-sensitive agglomeration variables and the population density control.

The two supply pooling measures also demonstrate few discernible and unambiguous impacts on production. The measure of potential manufactured input supply is significant in only one of the nine models, measuring and controlling devices in 2002, and there, against expectations, it is negative. The coefficient of the producer services variable only reaches conventional significance levels in two models (the other

[94] Like the concentration ratio measure of dominance, labor pooling is constructed as a ratio and enters the production function directly, without a logarithmic transformation. The estimated coefficient is interpreted as the percent change in output associated with a 100 percent rise from the sample mean in the distance-weighted fraction of the regional workforce employed in the top 15 occupations employed by that industry nationally. Two percent is roughly one standard deviation (see Table 6.3). The other four agglomeration economies are included in logarithmic form so their coefficients are elasticities.

two study industries in 2002) and is of opposite sign for those two industries. In most of the models, the coefficients of the two supply pooling variables are of opposite sign. Since the two variables are positively correlated (section 6.4 and Table 6.5), the most likely conclusion is that substantial colinearity between these two variables obscures the individual effects on establishment productivity.[95] Only in the 1997 model for metalworking machinery do both variables display positive estimated coefficients as expected and even for that sample the calculated impacts are slight.

Stronger results are obtained for the two knowledge spillover variables. Rubber and plastics plants located in regions with greater private sector innovative activity, as indicated by local patenting rates in relevant technology fields, are more productive, all else being equal, than plants sited in less innovative regions. The estimated effects are not huge but are large enough to be substantively important. In 1997 and 2002 a doubling of the regional patent rate in technology fields germane to rubber and plastics production is associated with a two percent surge in output. The estimated coefficient in 1992, approximately one eighth as large, may be an aberration, an artifact of changing assignment propensities for patent technology classifications, or else may indicate that the industry has only begun to benefit substantially from the private sector innovative climate in the last fifteen years or so.

The other two study industries display greater responses to regional patenting activity than the rubber and plastics industry. For 1992, the productivity gain to metalworking machinery establishments from a doubling of regional patenting is shy of eight percent; in 2002 the figure climbs past ten percent. The estimated impact on

[95] Neither several alternative formulae for these two variables nor the replacement of both measures with a single encompassing supply pool variable improves the quality or insightfulness of the model results.

production in the measuring and controlling devices industry has trended downward, from a nine percent improvement in 1992 to six percent in 2002 associated with twice the sample mean rate of patent approvals. Even considering the smallest of the estimated impacts for these two industries, the influence of regional patenting is enough to suggest a possible route by which local or regional policy measures might be able to influence productivity.

Academic research is considerably less important to the three study industries. A location proximate to research expenditures in those academic fields germane to the industry has a substantially smaller impact on production than the regional patenting rate. In the metalworking machinery models, local academic research is actually a negative factor. The high correlation between the academic research and manufactured input supply variables may obscure the results for rubber and plastics establishments (see section 6.4). Only for plants employed in manufacturing measuring and controlling devices does academic research yield a notable productivity improvement: doubling the index of nearby academic research raises output by one to two percent depending on the year of the sample. Higher technology industries, in this study represented by the measuring and controlling devices sector, may have more to gain from localized knowledge spillovers of basic research. It is also possible that the academic research indicator acts partially as a proxy for higher local land or employment costs, a factor that varies less across the samples of measuring and controlling device manufacturing establishments that are located primarily in dense and urban counties.

The relatively small influence of academic research recorded in these models is not entirely unexpected. Researchers generally have found it difficult to quantify the process of producing new knowledge. A large portion of the total impact of basic research is realized only in the very long term. Moreover, the measure of academic research expenditures used in this research pertains only to the knowledge creation function of universities and does not attempt to track the numerous other means (such as human capital creation and attraction, technology transfer, and local leadership) by which research universities influence economic performance in the surrounding region.

The absence of strong and consistent results for the agglomeration measures may be related to the over-representation in the samples of establishments located in regions with relatively substantial agglomeration possibilities. As discussed in section 6.2, the omission of plants located in regions with few industry establishments reduces the variation in the agglomeration measures and increases the tendency toward multicolinearity. Perhaps more importantly for the investigation of agglomeration influences, plants at the low end of the range of potential intra-industry agglomeration advantages are not included in the analysis. Although this exclusion is necessary to accommodate the principal research aim of examining regional industrial dominance, truncating the lower tail of the distribution of agglomeration potential may affect the estimation results pertaining to agglomeration economies.

Quite a few of the myriad interaction terms between agglomeration economies and standard inputs are significant, particularly those involving the labor pooling and knowledge spillover variables. These factor-altering characteristics of the agglomeration variables are somewhat more consistent over time than across industries, but vary in sign and significance between samples of the same industry as well. A couple of the more consistent effects are that labor pooling seems to restrain energy usage and local patenting tends to stimulate the use of additional labor inputs. The pattern of the interaction terms involving the two supply pooling variables reinforces the supposition of colinearity in that a significant positive interaction with one of the variables usually opposes a significant negative interaction between the same input and the other supply pooling variable.

Four of the five measures of potential agglomeration economies are defined spatially using the default distance decays and cutoffs established for each study industry (see section 5.7). Yet there is no reason to expect that spatial agglomeration economy effects should be identical across different spatial scales. Section 8.2 investigates how the estimated agglomeration influences vary with modifications of the default distance decay and cutoff parameters as an extension to the analysis presented in this chapter.

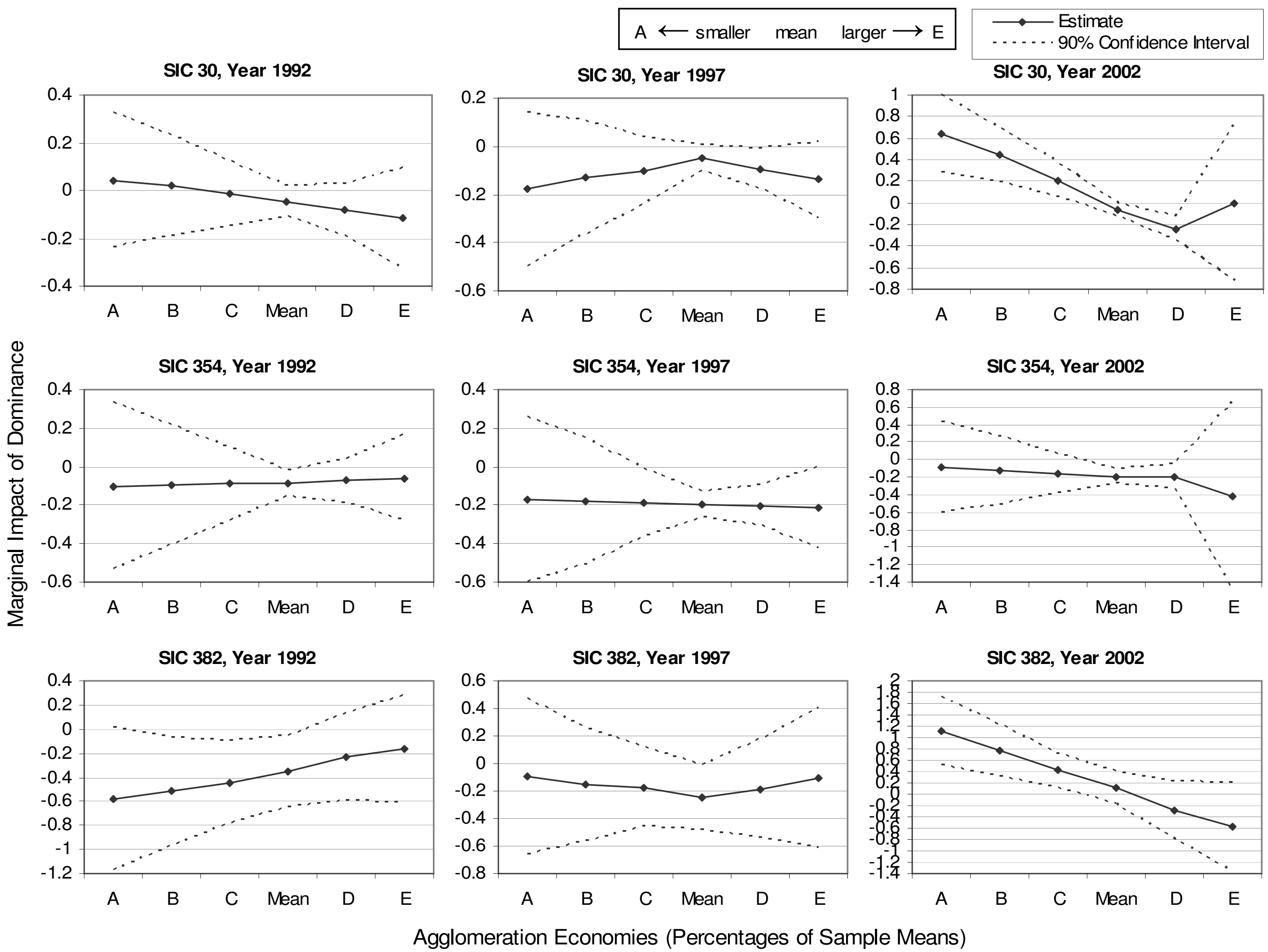
7.3.6. Dominance-Agglomeration Interactions

Turning to the interactions between dominance and agglomeration economies, the terms are small and mostly insignificant, not altogether a surprise given the mixed performance of the agglomeration variables as described in the preceding section. Few patterns emerge. In most of the models, the two supply pooling variables yield interaction terms with regional dominance that are of similar magnitude but opposite sign, again symptomatic of colinearity. For rubber and plastics plants, the interaction between dominance and private sector knowledge spillovers as indicated by local patenting rates is consistently negative whereas the interaction with academic research is positive. In locally dominated regions, small rubber and plastics plants may shift their attention from private sector to academic research, perhaps because the former is less accessible to non-dominators. The pattern does not hold for the other two study industries, however.

Figure 7.3 is constructed to be identical to Figure 7.2 except that it contains points that vary across the observed range of the agglomeration economy variables rather than the production inputs for each industry-year sample. As with the graphs in Figure 7.2, the points on the horizontal axes do not represent actual combinations of the agglomeration economies present in particular LMAs, but rather hypothetical regional endowments that approximate the spectrum from minimal to maximal available agglomeration economies.[96] The estimated impacts of regional industrial dominance vary less with the agglomeration regime than they do with input quantities. In two of the models, dominance has positive productivity effects in regions with few available agglomeration economies and negative effects where the levels of agglomeration economies are large. Regional industrial dominance may have the effect of hindering local establishments from accessing agglomeration economies, lowering productivity from expected levels primarily in those regions offering greater potential agglomeration benefits. Perhaps locally dominant firms in those areas that lack agglomeration economies create alternative advantages through local economic power (such as specialized training programs or applied research institutes) that then spill over to smaller firms in the regional industry. The 2002 models for rubber and plastics and measuring and controlling devices display this phenomenon. In one model, measuring and controlling devices in 1992, the opposite pattern occurs: the negative influence of dominance on production wanes with greater levels of agglomeration economies.

[96] While it might be interesting to consider combinations of dissimilar levels of the measured agglomeration economies, exploring the resulting volume and complexity of results would necessitate a second dissertation.

Figure 7.3. Marginal Impacts of Regional Industrial Dominance Across Range of Agglomeration Economies.



Most of the nine industry-year samples, however, demonstrate little change in dominance with different levels of potential agglomeration economies. Together with the observations and interpretations in the previous section pertaining to the impacts of agglomeration economies, this provides an answer to the second research question posed in the introduction. At least for the majority of study industries and years, it does not seem to be the case that regional industrial dominance inhibits the advantages that firms obtain from localized agglomeration economies. Because dominance and agglomeration are both explanatory variables in the production function model, the implications observed are symmetric with regard to the interaction between regional industrial dominance and agglomeration: the potential benefits of regional agglomeration economies are not dampened by regional industrial dominance, and the lower productivity of plants located in regionally dominated industries is not explained by their inability to benefit from agglomeration economies.

There are several possible explanations for the negative result. The most direct conclusion is that dominance does reduce establishment-level productivity, but the mechanism by which that outcome is realized is not the restriction of the ability of regional manufacturers to access local benefits of agglomeration. It is also possible that the samples may be too small, the translog model too complex, or the sought-after effects too subtle to perceive in the model results. The agglomeration economy indicators may not gauge their intended concepts adequately, may be weakened by the omission of plants in small regional industries, or may be indicative of the wrong agglomeration economies (for example, none of the five agglomeration variables measure capital or financing availability, one of the three pathways identified in Chapter Three as a possible mechanism for the influence of regional industrial dominance). Any one of these explanations, or all in combination, may be true to various degrees. Overall, however, this study does not support the idea that regional industrial dominance limits the abilities of manufacturers to capture local agglomeration economies.

7.4. Alternative Measures of Regional Industrial Dominance

Up to this point in the chapter, regional industrial dominance has been measured by the five-firm concentration ratio. Section 5.6 discussed three alternative measures of regional industrial dominance: the Herfindahl-Hirschman and Rosenbluth indices and the Gini coefficient. There are two main motives for investigating how substituting these for the concentration ratio measure of dominance alters the estimation results. First, there is no single accepted indicator of dominance. The concentration ratio is insensitive to the small end of the firm size distribution. The Rosenbluth index emphasizes small firms, whereas the Herfindahl-Hirschman index places extra weight on the largest firms. The Gini coefficient, unlike the three absolute measures, is a relative measure, corresponding to the degree of inequality in the firm size distribution irrespective of the number of firms in the regional industry. Testing different measures helps to gauge the robustness of the results with regard to the operationalization of the concept of regional industrial dominance. Second, the alternative indicators of dominance, in particular the Herfindahl-Hirschman index and the Gini coefficient, are less closely associated than the concentration ratio with regional industry scale. Their performance helps to ascertain whether it is reasonable to attribute the influence of the dominance variable observed in the model results to dominance rather than industry size.

Table 7.7 shows the estimates obtained by replacing the concentration ratio measure of dominance in the model with the three alternative indices. The original concentration ratio figures from Tables 7.4 through 7.6 are included for comparison. Only the coefficients of dominance, the square of dominance, and historical dominance are displayed. For the most part, the other variables change only slightly in response to the substitution of alternative measures of regional industrial dominance.[97] Note that the definitions of the dummy variables DE_z and SE_z remain unchanged, signifying the relatively large and small firms in each regional industry with reference to the five firms with the greatest value of shipments.

The coefficients of the three absolute measures of dominance match each other in terms of sign. They are negative in every estimated model but for measuring and controlling devices in 2002, for which the three estimated coefficients are positive. There are some discrepancies in the levels of significance, though overall there is far more agreement than disagreement. In the eight models in which absolute dominance negatively influences output, the coefficients of the Rosenbluth index are generally more significant than those of the Herfindahl-Hirschman index or the concentration ratio measure. In emphasizing the small end of the firm size distribution the Rosenbluth measure may more closely reflect the relationships among the smaller plants that tend to be more negatively affected by regional industrial dominance, or may reveal finer distinctions in industrial structure across regions. The single exception is that for metalworking machinery plants in 1992, only the concentration ratio measure of

[97] Some of the interaction term coefficients do change substantially, but without consistency or apparent patterns in terms of value or significance across the study industries, years, or dominance measures, suggesting random fluctuations rather than coherent relationships with respect to the alternative dominance measures. The model results including all regressors, as well as heteroskedasticity-corrected versions, are available from the author.

Table 7.7. Parameter Estimates for Alternative Measures of Regional Industrial Dominance.

SIC 30: Rubber and Plastics

Year		1992				1997				2002			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
D_C	γ_d	-0.0447	0.0389	-1.15	0.25	-0.0510	0.0332	-1.53	0.12	-0.0653	0.0369	-1.77	0.08
	δ_{dd}	-0.4514	0.2592	-1.74	0.08	-0.3009	0.2152	-1.40	0.16	-1.0574	0.2628	-4.02	0.00
	ρ_{dh}	-0.0119	0.0275	-0.43	0.67	-0.0020	0.0257	-0.08	0.94	-0.0595	0.0349	-1.71	0.09
D_H	γ_d	-0.1616	0.1119	-1.44	0.15	-0.0457	0.0856	-0.53	0.59	-0.4631	0.1047	-4.42	0.00
	δ_{dd}	0.2926	0.6952	0.42	0.67	-0.6452	0.6275	-1.03	0.30	-0.9326	0.9690	-0.96	0.34
	ρ_{dh}	-0.0127	0.0283	-0.45	0.65	-0.0162	0.0298	-0.54	0.59	-0.1170	0.0424	-2.76	0.01
D_R	γ_d	-0.9101	0.2383	-3.82	0.00	-0.5765	0.1863	-3.09	0.00	-1.0107	0.1676	-6.03	0.00
	δ_{dd}	3.5088	2.7137	1.29	0.20	1.7082	2.3833	0.72	0.47	1.9123	1.7470	1.09	0.27
	ρ_{dh}	-0.0752	0.0595	-1.26	0.21	-0.0605	0.0623	-0.97	0.33	-0.2060	0.0871	-2.36	0.02
D_G	γ_d	0.3673	0.0832	4.41	0.00	0.3341	0.0741	4.51	0.00	0.3499	0.0868	4.03	0.00
	δ_{dd}	0.9850	1.8003	0.55	0.58	-3.4604	1.4608	-2.37	0.02	-4.2601	1.3611	-3.13	0.00
	ρ_{dh}	-0.1467	0.0463	-3.17	0.00	-0.0747	0.0437	-1.71	0.09	-0.1850	0.0549	-3.37	0.00

SIC 354: Metalworking Machinery

Year		1992				1997				2002			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
D_C	γ_d	-0.0875	0.0413	-2.12	0.03	-0.2001	0.0407	-4.91	0.00	-0.1900	0.0518	-3.67	0.00
	δ_{dd}	0.2874	0.2866	1.00	0.32	0.8210	0.2773	2.96	0.00	-0.0518	0.3284	-0.16	0.87
	ρ_{dh}	-0.0179	0.0367	-0.49	0.63	-0.0143	0.0357	-0.40	0.69	0.2221	0.0425	5.23	0.00
D_H	γ_d	-0.1121	0.1055	-1.06	0.29	-0.1830	0.0796	-2.30	0.02	-0.2661	0.1012	-2.63	0.01
	δ_{dd}	-0.1567	0.8082	-0.19	0.85	-0.0867	0.5846	-0.15	0.88	-0.4970	0.5132	-0.97	0.33
	ρ_{dh}	-0.0235	0.0478	-0.49	0.62	-0.0732	0.0449	-1.63	0.10	0.1579	0.0588	2.69	0.01
D_R	γ_d	-0.2563	0.2254	-1.14	0.26	-0.6614	0.1731	-3.82	0.00	-0.7175	0.1757	-4.08	0.00
	δ_{dd}	-1.3148	1.7497	-0.75	0.45	2.3597	1.3853	1.70	0.09	0.4639	0.9159	0.51	0.61
	ρ_{dh}	-0.0419	0.0887	-0.47	0.64	-0.2542	0.0883	-2.88	0.00	0.1205	0.1348	0.89	0.37
D_G	γ_d	0.2912	0.0895	3.25	0.00	0.2169	0.0775	2.80	0.01	0.3920	0.1000	3.92	0.00
	δ_{dd}	-1.6921	1.2923	-1.31	0.19	-3.8613	1.1141	-3.47	0.00	-1.9572	1.4029	-1.40	0.16
	ρ_{dh}	-0.1956	0.0639	-3.06	0.00	-0.1670	0.0542	-3.08	0.00	0.0914	0.0724	1.26	0.21

SIC 382: Measuring and Controlling Devices

Year		1992				1997				2002			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
D_C	γ_d	-0.3532	0.1832	-1.93	0.05	-0.2499	0.1441	-1.73	0.08	0.1184	0.1793	0.66	0.51
	δ_{dd}	1.2189	0.9506	1.28	0.20	2.7059	1.2170	2.22	0.03	-3.0457	1.7200	-1.77	0.08
	ρ_{dh}	-0.0642	0.1100	-0.58	0.56	0.1107	0.0863	1.28	0.20	0.0283	0.1033	0.27	0.78
D_H	γ_d	-0.6369	0.2724	-2.34	0.02	-0.1969	0.2141	-0.92	0.36	0.5532	0.2702	2.05	0.04
	δ_{dd}	4.0213	1.3407	3.00	0.00	2.8435	1.2456	2.28	0.02	-4.1594	2.2360	-1.86	0.06
	ρ_{dh}	-0.0533	0.0673	-0.79	0.43	0.0101	0.0776	0.13	0.90	-0.1831	0.1056	-1.73	0.08
D_R	γ_d	-2.0502	0.6850	-2.99	0.00	-1.8161	0.6050	-3.00	0.00	0.0582	0.5339	0.11	0.91
	δ_{dd}	13.6820	5.8300	2.35	0.02	16.7564	5.9710	2.81	0.01	-4.4937	7.5179	-0.60	0.55
	ρ_{dh}	-0.1494	0.1097	-1.36	0.17	0.0119	0.1147	0.10	0.92	-0.1495	0.1384	-1.08	0.28
D_G	γ_d	0.4963	0.3390	1.46	0.14	1.1763	0.2813	4.18	0.00	0.4634	0.3075	1.51	0.13
	δ_{dd}	-2.3220	6.9458	-0.33	0.74	3.5000	3.6310	0.96	0.34	-6.6184	3.7694	-1.76	0.08
	ρ_{dh}	-0.3463	0.1946	-1.78	0.08	-0.1458	0.1428	-1.02	0.31	-0.1941	0.2258	-0.86	0.39

Note: D_C refers to the concentration ratio dominance measure, D_H to the Herfindahl-Hirschman index, D_R to the Rosenbluth index, and D_G to the Gini coefficient.

dominance is significant at conventional levels. Nevertheless, it is clear that the answer to the first research question supplied in section 7.3.4 holds using either the Rosenbluth or the Herfindahl-Hirschman index in place of the concentration ratio measure: regional industrial dominance is substantially and negatively associated with plant-level production.

The Gini coefficient yields results that contrast starkly with the other three measures of dominance. The estimated coefficients of the Gini measure are positive in each model, are generally highly significant and, save for the 1997 measuring and controlling devices sample, are relatively consistent in magnitude across the three study years. This corresponds with the observation made in Chapter Six that the sample means of the Gini coefficient are more stable over time than the means of the three absolute dominance indicators. The Gini coefficient, though used almost interchangeably with the Herfindahl-Hirschman index to measure industrial diversity (see section 2.4.2.3), carries distinct implications as an indicator of industrial dominance. Regional industrial inequality, operationalized independently of the local size of the industry, is positively associated with establishment production at the sample means of the other variables.[98]

The estimated coefficients are not easily compared directly across the four measures of regional industrial dominance because of the contrast in the methods of construction as well as differing sample properties (see Table 6.3). Table 7.8 presents the effect of an increase of one standard deviation in each dominance measure, reported as

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[98] One possible explanation for the contrast in outcomes between the Gini coefficient and the other dominance indicators is that the lesser degree of variation of the Gini coefficient across regions may reduce the stability of the regression results and thus produce estimates that differ widely from those obtained using absolute measures of regional industrial dominance. The consistency of the parameter estimates for the Gini coefficient measure across the nine industry-year samples, however, does not suggest such instability.

the percent change in output produced, calculated at the sample means of each of the independent variables. Table 7.8 also replicates the probability values of each dominance coefficient from Table 7.7 for convenience. In this format, it is straightforward to observe the consistently negative effects of the absolute dominance variables and the positive impact of inequality as measured by the Gini coefficient.

The greater significance of the Rosenbluth coefficients translates into larger estimated marginal effects. An increase of one standard deviation in the Gini coefficient shifts production by a percentage similar to that resulting from the corresponding change in the concentration ratio or Herfindahl-Hirschman measures, but, as noted earlier, the Gini coefficient tends to be less volatile over time than the other two measures. Overall, the magnitude of the figures in Table 7.8 emphasizes the importance of the influence that regional industrial dominance exerts on establishment productivity.

Table 7.8. Marginal Impacts of Alternative Dominance Indicators.

SIC	30			354			382		
Industry	rubber & plastics			metalworking machinery			measuring & controlling devices		
Year	1992	1997	2002	1992	1997	2002	1992	1997	2002
Dominance									
Concentration Ratio (D_C)	-0.85	-0.99	-1.30	-1.72	-4.18	-3.82	-6.49	-3.79	1.65
	(0.251)	(0.125)	(0.076)	(0.034)	(0.000)	(0.000)	(0.054)	(0.083)	(0.509)
Herfindahl-Hirschman (D_H)	-1.17	-0.35	-3.48	-0.92	-1.75	-2.69	-9.51	-2.38	6.81
	(0.149)	(0.593)	(0.000)	(0.288)	(0.022)	(0.009)	(0.020)	(0.358)	(0.041)
Rosenbluth (D_R)	-3.87	-2.60	-5.72	-1.23	-3.73	-5.14	-13.74	-10.70	0.37
	(0.000)	(0.002)	(0.000)	(0.256)	(0.000)	(0.000)	(0.003)	(0.003)	(0.913)
Gini (D_G)	1.81	1.69	1.92	2.11	1.54	2.85	2.56	6.66	3.22
	(0.000)	(0.000)	(0.000)	(0.001)	(0.005)	(0.000)	(0.143)	(0.000)	(0.132)

Note: Figures are percent changes in production with one standard deviation increase in dominance measure from sample mean.
Figures in parentheses are probability values of estimated coefficients of dominance, from Table 7.7.

Returning to Table 7.7, there is extensive variation in the squared dominance parameter, with swings in both sign and magnitude across the different dominance indicators. The coefficient of the square of dominance determines how the marginal effect of dominance changes with the level of dominance itself (i.e., the slopes of the lines in the graphs in Figure 7.1). For example, the positive coefficient for the square of the Rosenbluth dominance measure in the rubber and plastics models is responsible for reducing to some degree the impact of dominance on productivity in regions experiencing high levels of dominance compared to areas with intermediate regional industrial dominance. As with the concentration ratio measure, the estimated coefficients of the quadratic dominance term are not consistent across samples even within the same industry. It is possible that the nonlinear effects of dominance shift substantively over time. The statistical methods are most reliable, however, in the neighborhood of the point of approximation, the sample means. With the dominance variables mean-centered, the estimation procedures offer the greatest accuracy where the marginal effect of the square of dominance is zero.

The importance of historic dominance is relatively consistent across samples and dominance measures. For those industry-year samples which evidence little influence from historic concentration ratio dominance, the coefficients of the historic Herfindahl-Hirschman and Rosenbluth dominance terms normally also are small and insignificant. Metalworking machinery and rubber and plastics plants in 2002 are significantly impacted by the change in the five-firm concentration ratio over the prior 20 years; the change in the Herfindahl-Hirschman and Rosenbluth indices is correspondingly influential. One exception is the 1997 metalworking machinery sample, in which the negative but negligible influence of an historical increase in dominance on current productivity is amplified when the concentration ratio measure is replaced with the other absolute indicators of dominance. The Gini measure again displays distinctive behavior. For both rubber and plastics and metalworking machinery establishments, declines in regional industrial inequality over the past two decades (or historically high levels of inequality) are significantly associated with expanded productivity.[99] The same relationship holds in the measuring and controlling devices industry, though it reaches the 90 percent significance level only in 1992. The relative stability of the Gini coefficient over time suggests an explanation: absent fluctuations in the dominance measure arising from changes in the size of the local industry, adjustments in the Gini coefficient are less frequent, smaller, and may more commonly reflect substantive alterations in the structure of the regional industry than do shifts in the other three dominance measures. Finally, as with the concentration ratio measure of dominance, omission of the historic dominance variable does not alter the current dominance estimates to any great degree using the alternative indicators of dominance. The current effects of regional industrial dominance are not reliant on prior dominance levels.

So far, this section has examined regional industrial dominance only at the sample means of the other variables. Although it introduces additional complexity to the analysis, it is worth considering briefly how the estimated effects of the alternative dominance variables change with the volume of standard inputs and potential agglomeration economies. With respect to input quantities, the alternative dominance variables tend to behave in much the same way as the concentration ratio. The predominant pattern is that the marginal effects of dominance are more negative for

[99] The 2002 metalworking machinery sample is an exception.

smaller plants, those purchasing smaller quantities of capital, labor, energy, and materials.[100] The 1992 rubber and plastics model industry displayed in Figure 7.4 is representative. (Because there are so many permutations, the full set of graphs equivalent to Figures 7.2 and 7.3 for the other dominance measures is placed in Appendix 8.). The relationship also holds for the Gini dominance measure: the estimated marginal effects of dominance on productivity rise with increases in the volume of inputs. In the case of the Gini coefficient, since the marginal effects at the sample means are positive, the interpretation is that larger establishments obtain greater productivity enhancements with regional industrial inequality than the average plant, and smaller plants experience either a lesser increase or a decrease in production. The result confirms that the Gini coefficient does not indicate an entirely different phenomenon from the three absolute dominance variables, but rather a facet of regional industrial dominance measured on a different scale. The average plant's productivity is affected negatively by regional industrial dominance as measured by the concentration ratio, Herfindahl-Hirschman index, and Rosenbluth index, and positively as measured by the Gini coefficient. Yet for each indicator, the smaller the plant, the greater the negative outcome of dominance on productivity.

The alternative dominance measures also exhibit behavior similar to the concentration ratio with varying levels of agglomeration economies. For the most part, the estimated marginal impacts of the alternative dominance measures do not change very much with modifications in the levels of agglomeration economies, especially at the points nearest the mean that possess the greatest statistical validity and reliability.

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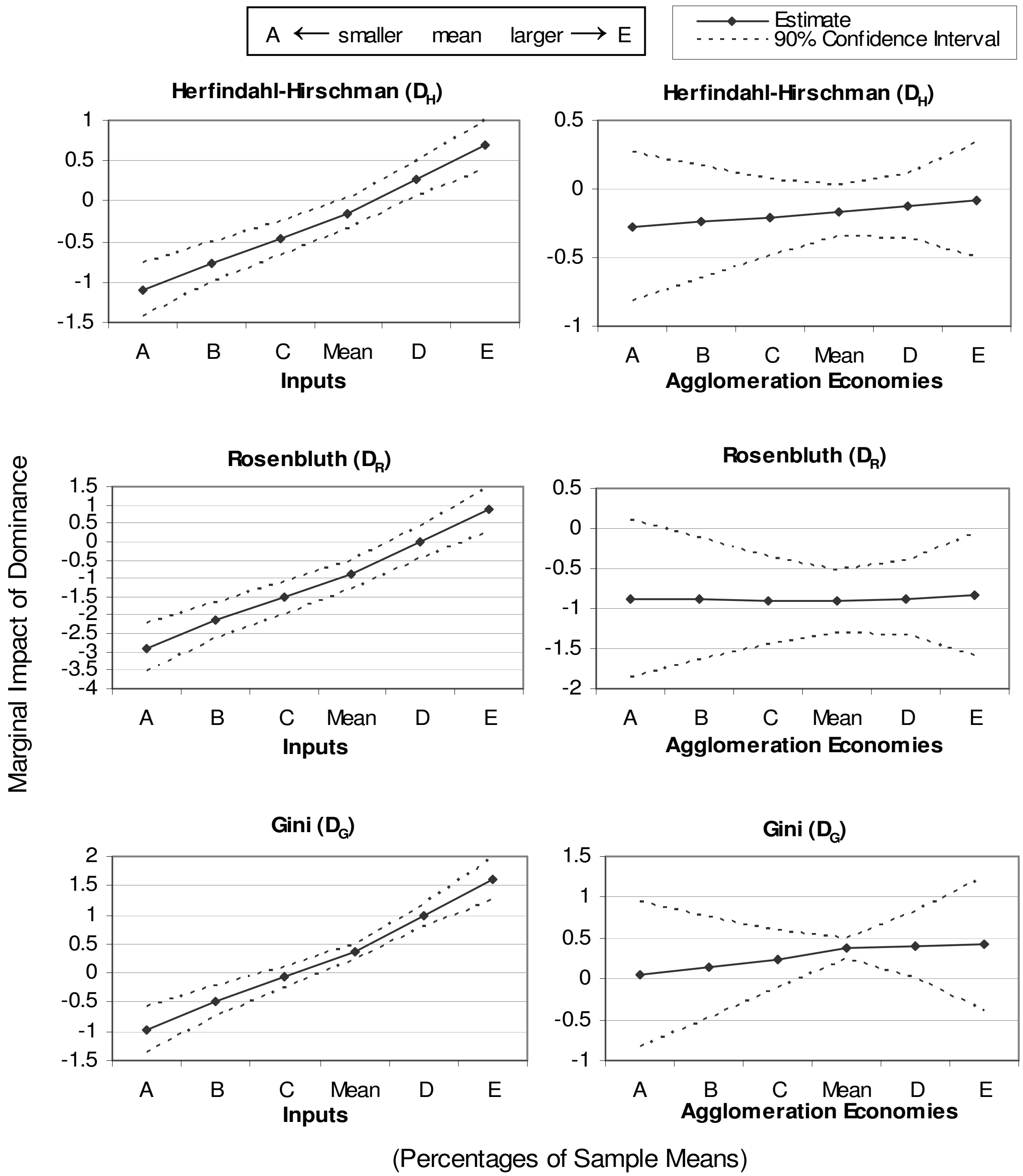
[100] There are a few exceptions: rubber and plastics in 1997 and measuring and controlling devices in 1997 and 2002 for the Herfindahl-Hirschman index, and measuring and controlling devices in 2002 for the Rosenbluth index.

Figure 7.4. Marginal Impacts of Alternative Regional Industrial Dominance Indicators Across Levels of Inputs and Agglomeration Economies for Rubber and Plastics (SIC 30), 1992.



The 1992 rubber and plastics model in Figure 7.4 typifies the prevailing pattern. There are more exceptions than with changes in input quantities, but the magnitude and direction of the shifts in the impacts of dominance that accompany variations in agglomeration economies are not consistent across industries, sample years, or dominance measures. The 2002 measuring and controlling devices and rubber and plastics samples are the only ones to evidence a dependable and substantive relationship, with absolute dominance of all three types (and Gini dominance as well for measuring and controlling devices) yielding negative productivity effects in regions with relatively large levels of available agglomeration economies. Nevertheless, the answer to the second research question remains the same for most of the industry-year pairs examined, that plants located in regionally dominated industries do not have reduced capacity to take advantage of local agglomeration economies.

7.5. Regional Dominance versus Industry Scale

As discussed in section 6.4, the five-firm concentration ratio measure of dominance is strongly negatively correlated with local industry scale as indicated by the count of firms. The estimated dominance coefficients by themselves are insufficient to ascertain empirically whether regional industrial dominance affects establishment-level productivity independently of local industry size.[101] There is, however, supplemental evidence useful in that assessment.

First, if the observed productivity effect of the concentration ratio measure of regional industrial dominance is an artifact of the negative correlation of dominance with

[101] As mentioned in Chapter Six, the theory presented earlier in the dissertation supports the dominance-based interpretation by suggesting direct causal links between dominance and firm performance.

local industry scale, then industry scale must act as a positive influence on production at individual plants. The most likely explanation for such a phenomenon is localization economies, or perhaps more general benefits of urbanization. But there are five variables in the models that measure agglomeration economies from localization, four of them also indirectly (via industry size) corresponding to urbanization. The population density control variable proxies urbanization levels directly. Therefore, the models already account for the effects of industry scale on establishment productivity through these independent variables.

Second, the alternative dominance indices provide additional indicators of the possible relationship between dominance and productivity. Although the Rosenbluth index is negatively correlated with industry size, the Herfindahl-Hirschman index is substantially less so. Yet the conclusion reached in the previous section is the same for all three absolute measures of regional industrial dominance: at the sample means, dominance yields strong negative effects on plant-level production. Neither the concentration ratio nor the Herfindahl-Hirschman index measure of dominance consistently exhibits a greater magnitude of estimated impacts than the other. Since it is a relative measure, the Gini coefficient does not exhibit a close association with regional industry scale (see Table 6.6), but it does display strong impacts on establishment productivity, in the positive direction at the sample means. If the regression relationship between dominance and output were due to the association of dominance with industry scale, then the Herfindahl-Hirschman index should result in smaller estimated marginal effects than the concentration ratio, and the Gini coefficient should be insignificant.

Additional tests corroborate the conclusion that regional industrial dominance rather than local industry size is responsible for the observed effects on plant production. Regressions conducted on samples created by increasing the minimum threshold number of firms in each regional industry reveal that the effects of dominance remain substantial and usually significant as well, implying that the effects regional industrial dominance are not due to an issue of minimum industry size. Substituting regional industrial employment for dominance in the model yields very different results for the variable directly and for the interaction terms with the standard inputs and agglomeration economies, suggesting that the association between dominance and industry scale does not direct the model outcomes. There is substantial multicolinearity introduced into the model if a direct measure of industry size (either regional industry employment or the number of firms) is added to the model as a control while the concentration ratio measure of dominance is retained. Yet the agglomeration economy variables that are significant without the industry size control decrease considerably in significance, and do not regain their significance if the variables involving dominance are omitted while the industry size measure is retained. This outcome indicates that the agglomeration variables successfully control for industrial size and localization economies in the preferred models. All of these experiments are indirect but further substantiate the claim that regional industrial dominance importantly influences establishment productivity independently of regional industry scale.

7.6. Summary

This chapter presented the results of the primary productivity model estimations. The approach extends previous production function research by examining the direct effects of regional industrial dominance on productivity and the indirect influence of dominance via imposing constraints on the capacity to benefit from localized agglomeration economies. Model tests justify the adoption of the relatively complex translog framework, decisively rejecting simpler functional forms as well as Hicks-neutral dominance and agglomeration economies throughout the nine industry-year samples.

In estimating models for three contrasting manufacturing industries, the analysis confirms that the industries exhibit distinct productivity patterns, particularly with regard to variables that control for local economic conditions such as unemployment, household income, and industrial diversity. The study industries are concentrated in different Census Regions, and the way in which productivity varies across the nation is specific to the particular industry. Urbanization, on the other hand, demonstrates a consistently positive though relatively small influence on production across all three industries. The measures of potential labor and supply pooling agglomeration economies display only weak and inconsistent effects on output. Either these measures fail to capture the agglomeration possibilities relative to the three study industries or the potential for local labor and supply pools does little to enhance production at the establishment level. In addition, it may be the case that the model estimates pertaining to the agglomeration variables are affected by the exclusion of plants located in regional industries with few firm members. The two knowledge spillover variables, patenting and academic research, do show beneficial effects on productivity. The influence of knowledge spillovers is strongest in the technology-intensive measuring and controlling device industry.

The most central and important results span the three study industries and the three sample years. The evidence decisively fails to reject the first research hypothesis: regional industrial dominance does reduce manufacturing productivity. Higher levels of absolute regional industrial dominance as indicated by the concentration ratio, Herfindahl-Hirschman index, or Rosenbluth index are associated with substantially lower levels of production calculated at the sample means for the plant and regional characteristics. The extent to which regional industrial dominance hampers production is greatest in the measuring and controlling industry and smallest for rubber and plastics establishments, suggesting that dominance may retard the production of more technology-intensive sectors to a greater degree. Small plants are more vulnerable than larger plants in each of the three study industries. When indicated with the Gini coefficient, a relative measure, regional industrial dominance has a positive effect on productivity at the sample means, but retains the pattern of having a more negative effect on smaller plants. Historic dominance conditions have only minimal impacts on production, and do not drive the contemporary effects of regional industrial dominance.

The estimation results do reject the second research hypothesis. Only in two of the nine samples do the interactions between dominance and agglomeration show the anticipated relationship of greater regional industrial dominance lowering productivity in regions with greater potential agglomeration economies. Establishments manufacturing rubber and plastics or measuring and controlling devices exhibit lower productivity than expected in regions with both substantial agglomeration potential and relatively high regional industrial dominance in the most recent sample year, but for the majority of the industry-year pairs there is little measured interaction between dominance and agglomeration. The alternative explanation that the data or the methodology are inadequate for detecting the connection between dominance and agglomeration cannot be ruled out as a possibility, particularly since three of the five agglomeration economy measures demonstrate little or no direct influence on establishment-level productivity, but the proposition that the second research hypothesis is incorrect is both substantive and consistent with the other results obtained throughout the analysis.

This study demonstrates the importance of regional industrial dominance in restraining the productivity of manufacturing plants, particularly those small enough to be dominated within their regional industry. Although most of the potential agglomeration economies exhibit little positive effect on establishment output, private sector knowledge spillovers do exert a large influence on production in metalworking machinery and measuring and controlling devices plants. Programs that encourage private research and support networks among regional knowledge producers and private sector consumers may provide a payback in terms of regional productivity. The conclusion regarding the second research question is unfortunate from the viewpoint of devising economic development policy. This analysis does not isolate the mechanism or set of mechanisms by which dominance generally influences productivity. Efforts to aid small firms in accessing regional agglomeration benefits or to substitute alternative methods of support may succeed in promoting production in particular industries and in certain economic circumstances, but may be ineffective in other settings. Additional research is required to determine the best and most widely applicable policy approaches for boosting plant productivity in dominated regional industries.

CHAPTER EIGHT: EXTENSIONS:
DISTANCE DECAY, REGION-WIDE DOMINANCE, AND PLANT SIZE

8.1. Introduction

This chapter extends the main analyses presented in Chapter Seven in three directions. The first examines the implications of varying the spatial decay and distance cutoff parameters for four of the agglomeration economy variables. The default decay specifications for the labor and supply pooling and academic research variables were chosen based on preliminary empirical testing of the nine industry-year samples, yet the estimated effects of potential agglomeration economies may vary with the spatial scale. The analysis reveals evidence that the labor pooling and academic research knowledge spillover agglomeration economies exist at broad spatial scales, but the results reported in the previous chapter hold, at least in qualitative terms, with regard to agglomeration economy variables defined using alternative spatial decay profiles.

The second extension considers the impacts of overall regional economic dominance, wherein a small group of firms dominates an entire regional economy. It is beyond the scope of this dissertation to analyze overall regional economic dominance separately from regional industrial dominance, as that task would merit a completely new modeling framework. The section focuses more narrowly on how overall economic dominance may condition the relationship between regional industry-specific dominance and productivity. The primary finding is that regional industrial and economy-wide dominance impact plant productivity separately from each other, such that the estimated effects of regional industrial dominance are not diminished by the inclusion of economy-wide dominance measures.

The final segment of the chapter investigates how the influences of regional industrial dominance and potential agglomeration economies on production vary with establishment size, with size measured either in absolute terms or relative to other regional plants. The empirical distributions of absolute versus relative establishment size are compared across the industry samples. Then the production function is modified to incorporate interaction terms between the dominance and agglomeration economy measures and dummy variables representing plant size categories and the models are re-estimated. The section demonstrates that relative size is beneficial for plant production, and that both large and very small establishments measured on an absolute size basis are more productive than industry averages. Yet it seems that these disparities are an intrinsic outcome of size, perhaps due to discrepancies in production technology, rather than the result of differential influences of external factors.

8.2. Extension One: Alternative Distance Decay Specifications

In the models described in the previous chapter, the same decay factor α was applied across agglomeration variables, and the maximum distance cutoff for each variable was set identically for each of the three study industries, in order to facilitate comparisons. It is possible, however, that agglomeration economy measures calculated under alternative decay profiles perform differently. In fact, as noted in section 7.3.5, the estimated effects of potential agglomeration economies are likely to vary with the spatial scale, as contrasting degrees of proximity reveal differences in the pattern of interfirm interactions. The extent of this variation also serves to indicate the robustness of the results detailed in Chapter Seven with regard to the spatial definition of the agglomeration variables.

The formulae for the labor pooling, manufactured input supplies, producer services, and academic research agglomeration variables each contain the distance decay factor ${d_{ck}}^{-\alpha}$, in which d_{ck} is the great circle distance (measured in miles) between the centroids of county c and the county k containing the target establishment, and α is the decay parameter that controls the rate at which the agglomeration influence is modeled as declining with distance (see section 5.7). The smaller the parameter α, the more gradual the decay. For the rubber and plastics and metalworking machinery industries, the default is $\alpha = 0.1$; the default decay of $\alpha = 1.0$ is much steeper for the measuring and controlling devices industry. For all three study industries, the default distance cutoff is 75 miles for the labor and supply pooling variables and 200 miles for academic research. Beyond this distance, the agglomeration influence on productivity is assumed to be zero. (The fifth agglomeration variable, based on patent data, is constructed at the regional level with no spatial decay.)

The models for each of the nine industry-year samples are re-estimated using agglomeration variables calculated under six spatial decay profiles.[102] Dominance is measured using the five-firm concentration ratio.[103] Three decay factors of 0.1, 0.5, and

[102] A large number of decay and distance cutoff parameters were tested that together span the spectrum from very narrow to broad patterns of spatial decay. These six profiles serve to illustrate the trends observed.
[103] The patterns depicted in this section are generally accurate in describing the models estimated with the alternative dominance measures as well. Those results are available from the author.

1.0 are imposed. Three different distance cutoffs are applied to the broadest decay factor ($\alpha = 0.1$): 50, 75, and 100 miles for the three labor and supply pooling variables, and 50, 200, and 300 miles for academic research. The maximum distance cutoff is unimportant with the steeper decays because the decay factor discounts the influence of agglomeration economies severely at intermediate to large distances. The sixth profile keeps the default distances of 75 miles for the labor and supply pooling measures and 200 miles for research, and combines the gradual decay factor of 0.1 for producer services with the strong decay factor of 1.0 for the remaining three spatially attenuating agglomeration variables. This final profile is the only one presented that incorporates dissimilar decay factors across agglomeration variables. It is included to test the observation made by Feser (2002) that proximity to producer services is important at a regional scale whereas proximity to manufactured inputs is not.

Tables 8.1 through 8.3 report the estimated coefficients for the four spatially attenuating agglomeration variables as the model is reevaluated under the six alternative spatial decay profiles, and Appendix 9 contains the descriptive statistics for the relevant permutations of the four agglomeration measures.[104] The manufactured inputs, producer services, and academic research (knowledge spillover) variables enter the model in logarithmic form, so the estimated coefficients are interpreted directly as elasticities at the sample means. Labor pooling is included in the production function directly because it is already in ratio form, so the estimated coefficients represent the percent change in output associated with a doubling of the labor pooling measure from the sample mean (see footnote 93 in Chapter Seven). Since the labor pooling measure is a ratio, the mean

[104] The other parameter coefficients are for the most part only slightly altered from the figures reported in Chapter Seven.

and standard deviation are not affected much by the spatial decay specification, and the coefficients may be compared usefully across the different decays.

As discussed in section 7.3.5, labor pooling is rarely significant under the default spatial decay profiles for the nine industry-year models. Altering the spatial decay or cutoff parameters typically does not increase the significance of the labor pooling variable. The explanation for the two counterexamples contained in Tables 8.1 through 8.3 is uncertain, though, since the estimated effects switch signs to become negative, perhaps spatially constrained concentrations of suitable labor (situated alongside employment opportunities) exert upward pressure on wages.[105] For those industry-year pairs in which the default labor pooling variable is significant and indicates a substantial impact on productivity, the alternative spatial decay profiles do not improve upon the strength of the coefficients or the magnitude of the effects. Within the measuring and controlling devices samples, there does seem to be a greater tendency for the estimated labor pooling coefficient to be negative with the tight decay factor of $\alpha = 1.0$ or a maximum distance restricted to 50 miles than when a broader gradient and larger cutoff distance are applied. This finding suggests that when they are large enough to be important, labor pooling advantages occur at the regional scale, contradicting earlier indications that labor pooling effects in this industry are relatively narrow in spatial extent (Feser 2002), or else labor pooling generally yields diseconomies rather than benefits. In light of additional research reporting labor pooling to be equally important (or equally insignificant) at both small and large spatial scales, albeit across a range of manufacturing industries and with different outcome measures and modeling techniques

[105] The two exceptions are with the maximum cutoff distance reduced to 50 miles for the 1997 measuring and controlling devices model, and with the combined decay factors (the sixth decay profile) for metalworking machinery establishments in 2002.

Table 8.1. Alternative Agglomeration Economy Spatial Decay Profiles for Rubber and Plastics (SIC 30).

	Labor Pooling (γ_{lp})	Manufactured Inputs (γ_{sp})	Producer Services (γ_{sd})	Research (γ_{rs})
Year: 1992				
α = 0.1, distance = 50, 50	0.518 (0.297)	0.011 (0.278)	0.005 (0.654)	0.000 (0.795)
α = 0.1, distance = 75, 200 (default)	0.900 (0.129)	0.005 (0.670)	-0.005 (0.657)	0.002 (0.862)
α = 0.1, distance = 100, 300	0.596 (0.345)	-0.007 (0.585)	-0.011 (0.356)	0.021 (0.045)
α = 0.5, distance = 75, 200	-1.440 (0.463)	0.238 (0.000)	-0.192 (0.000)	0.041 (0.138)
α = 1.0, distance = 75, 200	0.540 (0.180)	0.008 (0.362)	0.006 (0.401)	0.004 (0.334)
α = 1.0 except 0.1 for γ_{sd}, distance = 75, 200	0.289 (0.301)	0.014 (0.016)	-0.012 (0.121)	0.005 (0.227)
Year: 1997				
α = 0.1, distance = 50, 50	0.150 (0.587)	0.000 (0.971)	0.001 (0.936)	0.001 (0.467)
α = 0.1, distance = 75, 200 (default)	0.040 (0.902)	0.000 (0.976)	0.000 (0.967)	0.007 (0.315)
α = 0.1, distance = 100, 300	0.050 (0.889)	-0.003 (0.804)	-0.004 (0.743)	0.011 (0.214)
α = 0.5, distance = 75, 200	0.048 (0.870)	-0.006 (0.527)	0.009 (0.377)	0.012 (0.049)
α = 1.0, distance = 75, 200	-0.035 (0.869)	0.001 (0.869)	0.005 (0.435)	0.005 (0.179)
α = 1.0 except 0.1 for γ_{sd}, distance = 75, 200	-0.163 (0.295)	0.007 (0.173)	-0.008 (0.281)	0.004 (0.218)
Year: 2002				
α = 0.1, distance = 50, 50	0.681 (0.017)	-0.007 (0.524)	0.029 (0.009)	-0.002 (0.383)
α = 0.1, distance = 75, 200 (default)	0.686 (0.046)	-0.011 (0.410)	0.016 (0.222)	0.005 (0.502)
α = 0.1, distance = 100, 300	0.696 (0.067)	-0.010 (0.486)	0.014 (0.337)	0.015 (0.163)
α = 0.5, distance = 75, 200	0.772 (0.014)	-0.016 (0.201)	0.030 (0.012)	0.010 (0.180)
α = 1.0, distance = 75, 200	0.479 (0.037)	-0.011 (0.246)	0.022 (0.009)	0.007 (0.109)
α = 1.0 except 0.1 for γ_{sd}, distance = 75, 200	0.064 (0.700)	0.010 (0.075)	-0.008 (0.284)	0.009 (0.041)

Note: the first distance is the cutoff for labor pooling, manufactured inputs, and producer services; the second is for research.

Table 8.2. Alternative Agglomeration Economy Spatial Decay Profiles for Metalworking Machinery (SIC 354).

	Labor Pooling (γ_{lp})	Manufactured Inputs (γ_{sp})	Producer Services (γ_{sd})	Research (γ_{rs})
Year: 1992				
α = 0.1, distance = 50, 50	0.738 (0.355)	0.002 (0.896)	0.003 (0.837)	0.002 (0.232)
α = 0.1, distance = 75, 200 (default)	-0.512 (0.599)	0.024 (0.152)	-0.012 (0.364)	-0.029 (0.003)
α = 0.1, distance = 100, 300	-0.781 (0.480)	0.019 (0.318)	-0.009 (0.523)	-0.026 (0.046)
α = 0.5, distance = 75, 200	-0.224 (0.756)	0.014 (0.342)	0.001 (0.930)	-0.016 (0.084)
α = 1.0, distance = 75, 200	-0.199 (0.680)	0.010 (0.304)	0.000 (0.995)	-0.001 (0.911)
α = 1.0 except 0.1 for γ_{sd}, distance = 75, 200	-0.188 (0.667)	0.010 (0.142)	-0.011 (0.232)	0.002 (0.767)
Year: 1997				
α = 0.1, distance = 50, 50	-1.602 (0.029)	0.013 (0.365)	-0.020 (0.145)	0.000 (0.987)
α = 0.1, distance = 75, 200 (default)	-2.826 (0.003)	0.030 (0.086)	-0.046 (0.004)	0.005 (0.646)
α = 0.1, distance = 100, 300	-2.098 (0.057)	0.020 (0.356)	-0.033 (0.091)	0.003 (0.811)
α = 0.5, distance = 75, 200	-2.338 (0.003)	0.011 (0.490)	-0.026 (0.059)	0.013 (0.184)
α = 1.0, distance = 75, 200	-0.804 (0.132)	-0.001 (0.943)	-0.005 (0.622)	0.007 (0.184)
α = 1.0 except 0.1 for γ_{sd}, distance = 75, 200	-0.762 (0.030)	-0.002 (0.733)	-0.020 (0.016)	0.008 (0.167)
Year: 2002				
α = 0.1, distance = 50, 50	-0.196 (0.718)	-0.034 (0.030)	0.034 (0.032)	-0.005 (0.012)
α = 0.1, distance = 75, 200 (default)	0.060 (0.925)	-0.040 (0.026)	0.025 (0.138)	-0.019 (0.079)
α = 0.1, distance = 100, 300	-0.227 (0.754)	-0.063 (0.003)	0.021 (0.255)	0.017 (0.244)
α = 0.5, distance = 75, 200	0.231 (0.686)	-0.034 (0.046)	0.030 (0.049)	-0.024 (0.026)
α = 1.0, distance = 75, 200	-0.165 (0.707)	-0.016 (0.194)	0.018 (0.116)	-0.014 (0.037)
α = 1.0 except 0.1 for γ_{sd}, distance = 75, 200	-0.778 (0.019)	-0.003 (0.679)	0.003 (0.736)	-0.013 (0.043)

Note: the first distance is the cutoff for labor pooling, manufactured inputs, and producer services; the second is for research.

Table 8.3. Alternative Agglomeration Economy Spatial Decay Profiles for Measuring and Controlling Devices (SIC 382).

	Labor Pooling (γ_{lp})	Manufactured Inputs (γ_{sp})	Producer Services (γ_{sd})	Research (γ_{rs})
Year: 1992				
α = 0.1, distance = 50, 50	-0.311 (0.864)	0.008 (0.037)	-0.045 (0.139)	0.046 (0.003)
α = 0.1, distance = 75, 200	-0.934 (0.777)	-0.013 (0.057)	-0.060 (0.265)	0.040 (0.286)
α = 0.1, distance = 100, 300	1.032 (0.843)	-0.029 (0.081)	-0.066 (0.307)	0.061 (0.132)
α = 0.5, distance = 75, 200	1.398 (0.344)	-0.015 (0.036)	-0.033 (0.292)	0.050 (0.032)
α = 1.0, distance = 75, 200 (default)	1.326 (0.116)	-0.022 (0.026)	0.003 (0.896)	0.024 (0.044)
α = 1.0 except 0.1 for γ_{sd}, distance = 75, 200	1.293 (0.107)	-0.023 (0.020)	-0.026 (0.435)	0.023 (0.052)
Year: 1997				
α = 0.1, distance = 50, 50	-2.186 (0.065)	0.053 (0.027)	-0.035 (0.179)	0.028 (0.040)
α = 0.1, distance = 75, 200	-1.648 (0.414)	0.069 (0.043)	-0.047 (0.198)	0.005 (0.840)
α = 0.1, distance = 100, 300	0.571 (0.813)	0.058 (0.132)	-0.055 (0.136)	0.015 (0.549)
α = 0.5, distance = 75, 200	0.226 (0.821)	0.044 (0.076)	-0.023 (0.346)	0.029 (0.130)
α = 1.0, distance = 75, 200 (default)	0.365 (0.553)	0.028 (0.131)	-0.017 (0.345)	0.017 (0.092)
α = 1.0 except 0.1 for γ_{sd}, distance = 75, 200	0.571 (0.337)	0.021 (0.199)	-0.032 (0.308)	0.015 (0.158)
Year: 2002				
α = 0.1, distance = 50, 50	-1.344 (0.348)	-0.010 (0.746)	-0.026 (0.517)	0.017 (0.363)
α = 0.1, distance = 75, 200	-0.462 (0.842)	-0.009 (0.809)	-0.024 (0.655)	0.030 (0.228)
α = 0.1, distance = 100, 300	0.567 (0.859)	-0.003 (0.944)	0.034 (0.629)	0.001 (0.976)
α = 0.5, distance = 75, 200	-0.166 (0.904)	-0.007 (0.815)	-0.026 (0.450)	0.030 (0.243)
α = 1.0, distance = 75, 200 (default)	-0.268 (0.763)	-0.004 (0.872)	-0.017 (0.484)	0.011 (0.398)
α = 1.0 except 0.1 for γ_{sd}, distance = 75, 200	0.209 (0.801)	-0.011 (0.515)	-0.014 (0.673)	0.005 (0.684)

Note: the first distance is the cutoff for labor pooling, manufactured inputs, and producer services; the second is for research.

than this study (Rosenthal and Strange 2001; Renski 2006), there is as yet no general conclusion that can be stated with any degree of confidence.

The analysis of the two supply pooling measures across the differing spatial decay profiles continues to be disrupted by substantial colinearity. The additional spatial permutations add little to the results obtained under the default profiles. In most cases, the coefficients imply negligibly small impacts on production. In the few instances in which the manufactured input or producer services variable has a substantial influence, the estimated coefficients of the two supply pooling variables carry opposite signs.

The sixth spatial decay profile combines gradual decay in producer services with much sharper decay of the other three spatial agglomeration variables. The intention is to test Feser's (2002) finding that pools of producer services significantly aid productivity only with a relatively broad spatial decay, suggesting importance at a regional scale, whereas proximity to input suppliers is more important when highly localized. Unfortunately, the results obtained are inadequate to either support or deny the earlier discovery. The estimated coefficients with the combined spatial decay profile are similar to the others reported in Tables 8.1 through 8.3 in that they indicate minor impacts of opposing sign for the two supply pooling variables. The producer services coefficient is negative for all but one of the nine models. Whatever substantive effects may exist with regard to these two agglomeration economies are obscured by the colinearity between the measures. Nor does the combined decay profile yield superior results (in the sense of larger magnitudes or consistently positive signs) for the estimated coefficients of the other two agglomeration economies, labor pooling and research, in comparison to the default distance cutoffs and decay factors.

Proximity to academic research expenditures does not yield productivity benefits to the two traditional manufacturing industries studied in this analysis (see section 7.3.5). Measuring and controlling devices is the only one of the three industries to realize nontrivial benefits from nearby academic research calculated under the default spatial profiles, with a one or two percent gain associated with doubling the research measure from the sample mean.[106] The effect increases in importance with a less precipitous (i.e., a moderate rather than steep) distance decay. When the decay parameter α is reduced from 1.0 to 0.5, the magnitude of the impact approximately doubles. Further reduction to a decay factor of 0.1, however, diminishes the effect. In the rubber and plastics industry, though the default coefficients are quite small and may be complicated by correlation between the academic research and manufactured input supply measures, moderate spatial decay also maximizes the estimated benefits from research proximity. The different distance cutoffs do not form a completely consistent pattern across the nine industry-year samples, but larger spatial ranges are associated with greater elasticities more often than not. These findings are at odds with the result reported by Feser (2002) that changing the rate of distance decay affects the productivity influence of research very little. This research implies that proximity to academic research expenditures in fields related to the manufacturing industry in question is important, but benefits in productivity are produced over quite sizeable distances.

Although the estimated coefficients of the interaction terms between regional industrial dominance and agglomeration do change with the alternative decays and cutoff parameters used to construct the agglomeration measures, they vary within a very

[106] The productivity advantages gained in the other two industries from a doubling of the index of academic research are smaller than one percent or are negative.

restricted range, remaining small and mostly insignificant, and no particular patterns are discernible across the agglomeration decay profiles. There also is little change in the estimated marginal impact of other variables, such as regional industrial dominance or private sector knowledge spillovers (patenting).[107]

This extension demonstrates that the influence of potential agglomeration economies on production does not vary greatly according to the particular spatial decay contour imposed. Although not decisive, the empirical evidence suggests that the advantages from labor pooling and knowledge spillovers from academic research operate at relatively broad regional scales. The results obtained under the default specifications and reported in Chapter Seven are robust to the imposition of alternative spatial decay profiles. The qualitative interpretations of the model variables and interactions, and certainly the inferences regarding the main research hypotheses, do not change with alterations of the decay and distance cutoff parameters used to construct the four spatially attenuating agglomeration economy measures. This may be due in part to the lack of significance of many of the agglomeration economy measures.

8.3. Extension Two: Economy-Wide Dominance Controls

Regional economy-wide dominance may substantially impact the economic performance of individual establishments throughout the region. Indeed, the case Chinitz highlights in his original article concerns the domination of the Pittsburgh economy by large steel firms and the effects on firms in other industries located in the region. Like regional industrial dominance, the phenomenon of regional economy-wide dominance,

[107] Since these estimates are not central to the focus of this extension, they are not presented here, but they are available from the author.

with a single or small number of firms dominating an entire regional economy, has not been widely investigated in quantitative fashion. As described in section 2.2, previous quantitative empirical studies concerning concentration at the regional level primarily focus on average establishment size and regional industrial diversity. One exception, Renski (2006), finds that regional economy-wide dominance decreases the survival chances of new firms in several manufacturing industries, but increases survival rates slightly for professional services and data processing firms. This section operationalizes the notion of regional economy-wide dominance in a manner similar to industry-specific regional dominance and investigates how including regional economy-wide dominance as a control variable affects the modeling results presented in Chapter Seven.

Eight indicators of regional economy-wide dominance (DM_r, where r indexes the region) are calculated using the methods detailed in section 5.6 for regional industrial dominance. First, all the establishments within the *Longitudinal Research Database* that are part of the same multi-unit firm in a region (LMA) are aggregated, regardless of their industrial classification, in effect treating all regional manufacturing plants that are part of the same company as a single firm. Concentration ratio (DM_{Cr}), Herfindahl-Hirschman index (DM_{Hr}), Rosenbluth index (DM_{Rr}), and Gini coefficient (DM_{Gr}) measures of regional manufacturing dominance are then calculated using this population of regional firms, according to equations 5.10 through 5.13. Because there are many more firms in the manufacturing sector than in a single industry, the concentration ratio measure is calculated considering the 15 largest firms to be dominators.[108] Second, the

[108] As with the indicator for regional industrial dominance, the robustness of the concentration ratio measure of regional manufacturing dominance was tested by varying the number of top firms considered dominators. The results differed somewhat but not enough to alter the substance of the findings presented in this section (see also footnote 61 in Chapter Five). Alternative results are available from the author.

Longitudinal Business Database is used in precisely the same manner to create four additional measures of overall regional dominance (DO_{Cr}, DO_{Hr}, DO_{Rr}, and DO_{Gr}) that are also analogous to the regional industrial dominance indicators but incorporate both the manufacturing and non-manufacturing components of multi-plant firms within each region.[109,110] For these overall regional dominance measures, establishment employment is used to indicate firm size since the LBD does not contain the value of shipments. Appendix 10 provides descriptive information corresponding to the eight regional economy-wide dominance measures for each industry-year sample.[111]

As a preliminary step, Table 8.4 displays the Pearson correlation coefficients between the regional industry-specific and economy-wide dominance variables included in each model. The associations are chiefly positive, as would be expected for any regional industry that comprises a substantial portion of the manufacturing sector or the entire regional economy. In this study, such is normally (but not always) the case, due to the requirement that there be a minimum number of firms in the regional industry. The concentration ratio and Rosenbluth index measures of regional industrial dominance exhibit the strongest associations with the economy-wide dominance variables. For the most part, the correlations are not large enough to be troublesome for estimating and interpreting the regression system. The only coefficients exceeding 0.7 are for the

[109] The 2001 LBD is the latest version available at the time of analysis.

[110] The concentration ratio measure of overall regional dominance also considers the top 15 firms as dominators. Different numbers of top firms classified as dominators were also tried for the LBD-based concentration ratio, with results available from the author.

[111] These descriptive statistics are not useful for substantive interpretation. The means do not represent the average level of manufacturing dominance or overall dominance across the LMA regions in the study. The sample means are weighted averages of the level of manufacturing or overall dominance in each region, but because the units of analysis remain the firms in the study industries, the regions are effectively weighted by the number of firms they contain in the particular study industries.

Table 8.4. Pearson Correlation Coefficients Between Regional Industrial and Economy-Wide Dominance Variables.

SIC 30: Rubber and Plastics

		1992		1997		2002	
		Manufacturing Dominance	Overall Dominance	Manufacturing Dominance	Overall Dominance	Manufacturing Dominance	Overall Dominance
Concentratio Ratio	D_C	0.4617	0.5965	0.5150	0.6537	0.5389	0.6859
Herfindahl-Hirschman	D_H	0.1175	0.3404	0.1618	0.4690	0.2404	0.4962
Rosenbluth	D_R	0.7179	0.6483	0.7897	0.6743	0.7503	0.6510
Gini	D_G	0.1867	0.0525	0.2311	0.1315	0.1708	0.2301

SIC 354: Metalworking Machinery

		1992		1997		2002	
		Manufacturing Dominance	Overall Dominance	Manufacturing Dominance	Overall Dominance	Manufacturing Dominance	Overall Dominance
Concentratio Ratio	D_C	-0.0815	-0.0136	-0.1063	0.0900	0.1194	0.3098
Herfindahl-Hirschman	D_H	-0.0408	0.0004	-0.0467	0.1051	0.0333	0.2053
Rosenbluth	D_R	0.5605	0.5103	0.5039	0.4346	0.4267	0.4194
Gini	D_G	-0.0452	0.2387	-0.0201	0.2238	0.1539	0.3694

SIC 382: Measuring and Controlling Devices

		1992		1997		2002	
		Manufacturing Dominance	Overall Dominance	Manufacturing Dominance	Overall Dominance	Manufacturing Dominance	Overall Dominance
Concentratio Ratio	D_C	0.5150	0.4902	0.4019	0.4715	0.2426	0.4607
Herfindahl-Hirschman	D_H	0.3070	0.3784	0.4096	0.3678	0.2057	0.4024
Rosenbluth	D_R	0.4623	0.4823	0.3663	0.5448	0.3233	0.5565
Gini	D_G	0.1571	-0.0137	0.2078	0.1818	-0.0224	0.0376

Rosenbluth index measures of industrial and manufacturing-sector regional dominance in rubber and plastics industry samples.

Interestingly, the metalworking machinery samples demonstrate much weaker associations between industrial and economy-wide dominance than for the other two study industries, with many correlations close to zero. The explanation lies in the particular spatial pattern and plant size distribution of the industry. The spatial dispersion of metalworking machinery establishments makes it less likely that the industry's largest firms are located in regions that are home to the largest firms of other industries, producing relatively small correlations between the industry-specific and economy-wide dominance measures. In addition, metalworking machinery manufacturing establishments tend to be much smaller on average than rubber and plastics or measuring and controlling devices plants. The inequality is exaggerated in the estimation samples by the relatively dispersed geographic distribution of plants in the metalworking machinery industry: the elimination of regions with fewer than twelve establishments in the industry removes a much smaller percentage of the small plants in the metalworking machinery industry than in the other two industries examined in this analysis. The average plant size in the metalworking machinery samples is less than half that of rubber and plastics and only a third as large as for measuring and controlling devices (see Table 6.1). Firms that may dominate the metalworking machinery manufacturing industry in a region are rarely sizeable enough to be dominators with respect to the entire manufacturing sector or the regional economy as a whole.

For each industry-year pair and type of regional industrial dominance measure, two variations of the four-equation system combining the translog production function and the three associated cost share equations are estimated. The first version adds a control variable for regional manufacturing dominance to the production function, and the second adds overall regional dominance instead. The economy-wide dominance indicators match the type used for regional industrial dominance in each model, in order to keep the number of permutations within a reasonable range for analysis. Table 8.5 reveals the estimated impact on output of an increase of one standard deviation in each dominance measure, with all other variables maintained at the sample means. The effects are compared with those from the base models (repeated from Chapter Seven) that do not contain an economy-wide dominance variable. Only the dominance variable coefficients are displayed. The inclusion of an economy-wide dominance variable does not substantially change the quadratic regional industrial dominance term, or the interactions between regional industrial dominance and the agglomeration economies and standard production inputs.[112] The remaining variables are essentially unaffected as well. The coefficient estimates are provided in Appendix 10.

The first result of interest is that the effects of regional industrial dominance on production are fairly robust with respect to the inclusion of economy-wide dominance control variables. Declines in the magnitude of the influence of intra-industry dominance on production are relatively small in most of the models and do not drastically affect significance levels; in some cases, the industry-specific dominance coefficients even increase in absolute value. The largest reductions occur when the Rosenbluth index is used to measure dominance, and these are likely the consequence of colinearity between

[112] In the regression for measuring and controlling devices in 1992 using concentration ratio dominance measures, the coefficient of the dominance-squared term does change sign when the overall regional dominance control is included, but neither estimated parameter is significant. These estimates are available from the author.

Table 8.5. Marginal Impacts of Regional Industrial and Economy-Wide Dominance.

SIC 30: Rubber and Plastics

Year		1992			1997			2002		
Economy-Wide Dominance Type		None	Manufacturing	Overall	None	Manufacturing	Overall	None	Manufacturing	Overall
D_C	industry-specific	-0.85 (0.251)	-0.69 (0.366)	-0.49 (0.547)	-0.99 (0.125)	-1.20 (0.071)	-1.02 (0.141)	-1.30 (0.076)	-1.41 (0.060)	-1.08 (0.153)
	economy-wide		-0.48 (0.326)	-0.74 (0.247)		0.55 (0.174)	0.07 (0.914)		0.31 (0.485)	-0.75 (0.275)
D_H	industry-specific	-1.17 (0.149)	-1.10 (0.179)	-1.13 (0.187)	-0.35 (0.593)	-0.29 (0.652)	-0.28 (0.680)	-3.48 (0.000)	-3.54 (0.000)	-3.25 (0.000)
	economy-wide		-0.47 (0.200)	-0.09 (0.871)		-0.28 (0.404)	-0.18 (0.731)		0.22 (0.549)	-0.72 (0.177)
D_R	industry-specific	-3.87 (0.000)	-2.72 (0.025)	-2.81 (0.011)	-2.60 (0.002)	-2.48 (0.006)	-1.45 (0.117)	-5.72 (0.000)	-5.73 (0.000)	-5.26 (0.000)
	economy-wide		-1.06 (0.084)	-1.75 (0.018)		-0.22 (0.700)	-2.00 (0.003)		0.01 (0.987)	-0.99 (0.150)
D_G	industry-specific	1.81 (0.000)	1.81 (0.000)	1.82 (0.000)	1.69 (0.000)	1.61 (0.000)	1.66 (0.000)	1.92 (0.000)	1.85 (0.000)	1.95 (0.000)
	economy-wide		0.08 (0.860)	1.90 (0.001)		0.56 (0.121)	1.35 (0.003)		0.45 (0.245)	2.02 (0.001)

SIC 354: Metalworking Machinery

Year		1992			1997			2002		
Economy-Wide Dominance Type		None	Manufacturing	Overall	None	Manufacturing	Overall	None	Manufacturing	Overall
D_C	industry-specific	-1.72 (0.034)	-1.82 (0.027)	-1.76 (0.030)	-4.18 (0.000)	-4.28 (0.000)	-4.13 (0.000)	-3.82 (0.000)	-3.59 (0.001)	-3.70 (0.000)
	economy-wide		-0.51 (0.443)	-1.09 (0.240)		-0.39 (0.532)	-2.27 (0.007)		1.42 (0.045)	-2.56 (0.026)
D_H	industry-specific	-0.92 (0.288)	-0.97 (0.267)	-0.97 (0.269)	-1.75 (0.022)	-1.75 (0.022)	-1.62 (0.035)	-2.69 (0.009)	-2.31 (0.024)	-2.65 (0.009)
	economy-wide		-0.42 (0.461)	-0.41 (0.683)		-0.02 (0.971)	-0.97 (0.219)		2.29 (0.000)	-1.21 (0.204)
D_R	industry-specific	-1.23 (0.256)	0.31 (0.787)	-0.07 (0.951)	-3.73 (0.000)	-3.03 (0.003)	-3.05 (0.002)	-5.14 (0.000)	-5.09 (0.000)	-4.42 (0.000)
	economy-wide		-3.94 (0.000)	-3.71 (0.000)		-2.59 (0.004)	-2.68 (0.000)		-0.78 (0.460)	-4.38 (0.000)
D_G	industry-specific	2.11 (0.001)	2.11 (0.001)	1.97 (0.003)	1.54 (0.005)	1.36 (0.013)	0.95 (0.091)	2.85 (0.000)	2.57 (0.000)	2.79 (0.000)
	economy-wide		0.84 (0.090)	0.78 (0.281)		1.77 (0.001)	3.23 (0.000)		2.39 (0.000)	0.84 (0.369)

SIC 382: Measuring and Controlling Devices

Year		1992			1997			2002		
Economy-Wide Dominance Type		None	Manufacturing	Overall	None	Manufacturing	Overall	None	Manufacturing	Overall
D_C	industry-specific	-6.49 (0.054)	-6.97 (0.039)	-5.76 (0.088)	-3.79 (0.083)	-4.89 (0.028)	-4.13 (0.061)	1.65 (0.509)	0.53 (0.835)	1.76 (0.484)
	economy-wide		-3.39 (0.077)	-6.85 (0.018)		-3.99 (0.016)	-2.81 (0.143)		-3.27 (0.033)	-1.25 (0.574)
D_H	industry-specific	-9.51 (0.020)	-10.15 (0.032)	-4.28 (0.338)	-2.38 (0.358)	-2.30 (0.387)	-2.32 (0.370)	6.81 (0.041)	6.68 (0.049)	6.98 (0.039)
	economy-wide		0.36 (0.794)	-6.60 (0.005)		-0.15 (0.894)	-1.11 (0.473)		-0.27 (0.835)	-0.50 (0.782)
D_R	industry-specific	-13.74 (0.003)	-13.64 (0.003)	-13.62 (0.003)	-10.70 (0.003)	-10.73 (0.003)	-9.35 (0.011)	0.37 (0.913)	-0.43 (0.902)	0.29 (0.931)
	economy-wide		-1.30 (0.557)	-0.76 (0.694)		-1.08 (0.471)	-2.93 (0.152)		-1.84 (0.241)	-1.58 (0.476)
D_G	industry-specific	2.56 (0.143)	2.84 (0.106)	2.35 (0.219)	6.66 (0.000)	6.66 (0.000)	6.06 (0.000)	3.22 (0.132)	3.19 (0.136)	3.61 (0.101)
	economy-wide		-2.03 (0.132)	0.51 (0.784)		0.49 (0.691)	1.33 (0.349)		-1.89 (0.210)	-1.28 (0.459)

Note: Figures are percent changes in production with one standard deviation increase in dominance measure from the sample mean. Figures in parentheses are probability values of estimated coefficients of dominance, from Tables A.10.2, A.10.3, and A.10.4.

the industry-specific and economy-wide dominance variables.[113] The lack of connection between the effects of the two types of dominance is especially evident in the metalworking machinery industry, which, because of the low correlations present in the estimation samples, yields perhaps the best indication of the interplay between industrial and economy-wide dominance. The introduction of economy-wide dominance measures affects the estimated impacts of regional industrial dominance on the production of metalworking machinery establishments very little.

Regional economy-wide dominance is an important influence on establishment productivity in its own right in many of the models, though the results vary widely across the sample years and industries. Measured with concentration ratios, regional manufacturing dominance negatively impacts production in measuring and controlling devices plants. The magnitude of the effect rivals that of regional industrial dominance (and exceeds it for the 2002 sample), with production declines of three to four percent associated with a standard deviation increase in regional manufacturing dominance (a rise of about 12 percent in the total manufacturing shipment value represented by the top 15 firms). The estimated coefficients for the other two industries, however, are much smaller, are not significant, and are positive more often than not for the latter two study years. Overall regional dominance demonstrates a more consistently negative connection with output across the nine industry-year samples, though the magnitude of the effects is still largest in the measuring and controlling devices industry.[114]

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[113] The 1992 measuring and controlling devices model using the Herfindahl index may be considered to be the exception that proves the rule.

[114] When the number of top firms used to calculate the concentration ratio measures is varied, the prevailing pattern is for the estimated coefficient of economy-wide dominance to be greater in magnitude and more significant with a greater number of firms considered dominators, but there are exceptions. The estimations demonstrating this relationship are not included in Table 8.5 but may be obtained from the author.

The relationships change to some degree when the three alternative dominance indicators are considered. The signs of the estimated coefficients for the three absolute dominance measures normally coincide for a particular industry-year pair, but often are of disparate magnitudes. This is especially true for the Rosenbluth index indicator of dominance as compared to the concentration ratio and Herfindahl measures. For instance, in the 1992 metalworking machinery model, the impact of a standard deviation rise in regional manufacturing dominance as measured by the concentration ratio is a decline in output of about one half of one percent; when measured with the Rosenbluth index, the drop is nearly four percent. For measuring and controlling devices plants in 1992, the estimated influence of overall regional dominance on production is nearly ten times as large calculated with the concentration ratio or Herfindahl index than with the Rosenbluth measure.

As is true throughout the analysis, the Gini coefficient displays markedly different behavior. The influence of regional inequality on production at the sample means typically is positive. Although the magnitude of the impact is insignificant within the measuring and controlling devices samples, the effects on establishments within the other two industries are substantial. For all three study years, a rise in overall regional dominance as measured with the Gini coefficient yields significant production benefits in the rubber and plastics industry, and regional manufacturing dominance positively affects metalworking machinery output.

The evidence demonstrates that regional industrial dominance and regional economy-wide dominance are distinct phenomena. Economy-wide dominance influences plant-level productivity independently of regional industrial dominance, but the relationship presents considerable complexities. For example, within the nine industry-year samples, there is no clear indication as to whether economy-wide dominance across the manufacturing sector or across both the manufacturing and non-manufacturing portions of the economy is more influential. It is possible that a portion of the difference between the measured influence of regional manufacturing dominance and overall regional dominance may be the result of the latter variable being based on employment rather than total shipment value data. Regional economy-wide dominance probably deserves to be investigated more thoroughly as the primary variable of interest in a separate quantitative study. Within this dissertation, however, the focus is on regional industrial dominance. In that respect, the qualitative conclusions regarding the importance of regional industrial dominance reached in Chapter Seven hold up against competition from the concept of economy-wide dominance.

8.4. Extension Three: Plant Size Interactions

The importance of regional industrial dominance for plant productivity may depend on the size of a particular establishment. For instance, larger plants possess greater internal resources and thus may benefit to a lesser degree than smaller establishments from localized advantages arising from external agglomerations of activity. Small firms that support less job specialization and offer fewer promotion opportunities may be more susceptible to employee poaching by a locally dominant company, so that their productivity is hampered by regional industrial dominance more than larger neighboring firms (see section 3.3). It is worth investigating whether plant size helps to determine the influence that regional industrial dominance and potential regional agglomeration economies have on production.

The production function modeling framework is easily modified to accommodate an examination of the possible conditioning relationships that plant size may have with regard to regional industrial dominance and agglomeration economies. Two dummy variables signifying dominator and dominated firms (*DE* and *SE*) are already included in the production function detailed in equation 5.20; equation 8.1 adds multiplicative terms that interact the binary indicators with the dominance and agglomeration variables:

$$
\begin{aligned}
\ln Q = {} & \alpha_0 + \alpha_k \ln K + \alpha_l \ln L + \alpha_e \ln E + \alpha_m \ln M \\
& + \frac{1}{2}\beta_{kk}(\ln K)^2 + \frac{1}{2}\beta_{ll}(\ln L)^2 + \frac{1}{2}\beta_{ee}(\ln E)^2 + \frac{1}{2}\beta_{mm}(\ln M)^2 \\
& + \beta_{kl} \ln K \ln L + \beta_{ke} \ln K \ln E + \beta_{km} \ln K \ln M \\
& + \beta_{le} \ln L \ln E + \beta_{lm} \ln L \ln M + \beta_{em} \ln E \ln M \\
& + \gamma_d D + \gamma_{lp} LP + \gamma_{sp} \ln SP + \gamma_{sd} \ln SD + \gamma_{rs} \ln RS + \gamma_{ps} \ln PS \\
& + \frac{1}{2}\delta_{dd}\left(D^2\right) + \delta_{dlp}\left(D \cdot LP\right) + \delta_{dsp} D \ln SP \\
& + \delta_{dsd} D \ln SD + \delta_{drs} D \ln RS + \delta_{dps} D \ln PS \\
& + \lambda_{dk} D \ln K + \lambda_{dl} D \ln L + \lambda_{de} D \ln E + \lambda_{dm} D \ln M \\
& + \lambda_{lpk} LP \ln K + \lambda_{lpl} LP \ln L + \lambda_{lpe} LP \ln E + \lambda_{lpm} LP \ln M \\
& + \lambda_{spk} \ln SP \ln K + \lambda_{spl} \ln SP \ln L + \lambda_{spe} \ln SP \ln E + \lambda_{spm} \ln SP \ln M \\
& + \lambda_{sdk} \ln SD \ln K + \lambda_{sdl} \ln SD \ln L + \lambda_{sde} \ln SD \ln E + \lambda_{sdm} \ln SD \ln M \\
& + \lambda_{rsk} \ln RS \ln K + \lambda_{rsl} \ln RS \ln L + \lambda_{rse} \ln RS \ln E + \lambda_{rsm} \ln RS \ln M \\
& + \lambda_{psk} \ln PS \ln K + \lambda_{psl} \ln PS \ln L + \lambda_{pse} \ln PS \ln E + \lambda_{psm} \ln PS \ln M \\
& + \nu_{de} DE + \nu_{se} SE + \nu_{cr1} CR1 + \nu_{cr2} CR2 + \nu_{cr3} CR3 \\
& + \nu_{pop} \ln POP + \nu_{ue} UE + \nu_{inc} \ln INC + \nu_{dv} DV \\
& + \rho_{dh} DH + \rho_{dvh} DVH \\
& + \kappa_{dde} D \cdot DE + \kappa_{dse} D \cdot SE + \kappa_{ddde} D^2 \cdot DE + \kappa_{ddse} D^2 \cdot SE \\
& + \kappa_{lpde} LP \cdot DE + \kappa_{lpse} LP \cdot SE + \kappa_{spde} \ln SP \cdot DE + \kappa_{spse} \ln SP \cdot SE \\
& + \kappa_{sdde} \ln SD \cdot DE + \kappa_{sdse} \ln SD \cdot SE + \kappa_{rsde} \ln RS \cdot DE + \kappa_{rsse} \ln RS \cdot SE \\
& + \kappa_{psde} \ln PS \cdot DE + \kappa_{psse} \ln PS \cdot SE + \varepsilon
\end{aligned}
\tag{8.1}
$$

.

Once the model is estimated substituting equation 8.1 for equation 5.20 in the four-equation system (the cost share equations do not change from equation 5.21), the marginal effects of regional industrial dominance and agglomeration economies may be calculated for each of the three size groups: establishments within dominator firms, establishments within dominated firms, and plants that do not belong to either category. The effects of the two dummy variables may also be computed to produce a measure of the average cost or benefit to productivity of belonging to each dominance classification.

Plant size may be measured either relative to competitor enterprises or in absolute terms. Some studies do adopt relative size measures, such as Feser (2001a), in which size categories are defined by sample quartiles (see section 3.3 for additional examples). Absolute size classifications are more common in research applications, however, and are used nearly exclusively in policy settings, chiefly because measuring relative size requires detailed knowledge pertaining to the entire sample or population. It may be reasonable on theoretical grounds to suppose that relative size affects the influence of regional industrial dominance on production whereas absolute size is more pertinent to the benefits to be gained from localized agglomeration economies, but there is no direct empirical evidence available as to whether this conjecture holds in practice.

The dummy variables *DE* and *SE* that classify establishments as part of dominator or dominated firms signify relative size within the regional industry. Equation 8.2 modifies the production function again, replacing the two binary variables with a single dummy indicator (*SM*) that identifies the small plants in each estimation sample:

$$
\begin{aligned}
\ln Q = {} & \alpha_0 + \alpha_k \ln K + \alpha_l \ln L + \alpha_e \ln E + \alpha_m \ln M \\
& + \frac{1}{2}\beta_{kk}(\ln K)^2 + \frac{1}{2}\beta_{ll}(\ln L)^2 + \frac{1}{2}\beta_{ee}(\ln E)^2 + \frac{1}{2}\beta_{mm}(\ln M)^2 \\
& + \beta_{kl} \ln K \ln L + \beta_{ke} \ln K \ln E + \beta_{km} \ln K \ln M \\
& + \beta_{le} \ln L \ln E + \beta_{lm} \ln L \ln M + \beta_{em} \ln E \ln M \\
& + \gamma_d D + \gamma_{lp} LP + \gamma_{sp} \ln SP + \gamma_{sd} \ln SD + \gamma_{rs} \ln RS + \gamma_{ps} \ln PS \\
& + \frac{1}{2}\delta_{dd}\left(D^2\right) + \delta_{dlp}\left(D \cdot LP\right) + \delta_{dsp} D \ln SP \\
& + \delta_{dsd} D \ln SD + \delta_{drs} D \ln RS + \delta_{dps} D \ln PS \\
& + \lambda_{dk} D \ln K + \lambda_{dl} D \ln L + \lambda_{de} D \ln E + \lambda_{dm} D \ln M \\
& + \lambda_{lpk} LP \ln K + \lambda_{lpl} LP \ln L + \lambda_{lpe} LP \ln E + \lambda_{lpm} LP \ln M \\
& + \lambda_{spk} \ln SP \ln K + \lambda_{spl} \ln SP \ln L + \lambda_{spe} \ln SP \ln E + \lambda_{spm} \ln SP \ln M \\
& + \lambda_{sdk} \ln SD \ln K + \lambda_{sdl} \ln SD \ln L + \lambda_{sde} \ln SD \ln E + \lambda_{sdm} \ln SD \ln M \\
& + \lambda_{rsk} \ln RS \ln K + \lambda_{rsl} \ln RS \ln L + \lambda_{rse} \ln RS \ln E + \lambda_{rsm} \ln RS \ln M \\
& + \lambda_{psk} \ln PS \ln K + \lambda_{psl} \ln PS \ln L + \lambda_{pse} \ln PS \ln E + \lambda_{psm} \ln PS \ln M \\
& + \nu_{sm} SM + \nu_{cr1} CR1 + \nu_{cr2} CR2 + \nu_{cr3} CR3 \\
& + \nu_{pop} \ln POP + \nu_{ue} UE + \nu_{inc} \ln INC + \nu_{dv} DV \\
& + \rho_{dh} DH + \rho_{dvh} DVH \\
& + \kappa_{dsm} D \cdot SM + \kappa_{ddsm} D^2 \cdot SM + \kappa_{lpsm} LP \cdot SM + \kappa_{spsm} \ln SP \cdot SM \\
& + \kappa_{sdsm} \ln SD \cdot SM + \kappa_{rssm} \ln RS \cdot SM + \kappa_{pssm} \ln PS \cdot SM + \varepsilon
\end{aligned} \tag{8.2}
$$

The marginal effects of regional industrial dominance and agglomeration economies may be computed separately for small and large (i.e., not small) establishments using equation 8.2 as the production function.

There are several reasons to test a range of absolute size criteria for determining which establishments are "small". There is substantial variety in definitions of small businesses across various nations and policies.[115] The way in which establishment scale

[115] Within the United States, the small business size standards of the Small Business Administration are industry-specific, but for most manufacturing industries the criterion is that a small establishment employs no more than 500 full-time equivalent workers (United States Small Business Administration 2006). For compliance purposes, the Environmental Protection Agency considers small businesses to be those with a maximum of 100 employees (United States Environmental Protection Agency 2000). The Small Business Job Protection Act of 1996 defines small businesses as having 100 or fewer employees for the purpose of establishing employee savings options, whereas the maximum size for companies to gain exemption from

conditions the influence of dominance and agglomeration opportunities on productivity may differ according to the size threshold considered. In addition, altering the definition of "small" may yield a sense of the robustness of the results obtained. The models in this extension are estimated with three different definitions of small establishments based on absolute size: those plants employing no more than 15, 50, or 250 employees.[116,117]

Table 8.6 presents sample descriptive information about the size categories used in this section.[118] Very few plants in any of the industries qualify as large when the criterion is to employ more than 250 workers. This is due partly to considering establishment-specific rather than firm-wide employment totals, but the main reason is that the three study industries have highly skewed plant size distributions (as do most industries). The great majority of businesses fall within the definitions of "small" used in many policy contexts. Small business applicability thresholds are often set high in order to boost the population of firms included in a program or subject to a set of guidelines. Even when the maximum size is reduced to 50 employees, more than 80 percent of the sample metalworking machinery manufacturing establishments fit into the small

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the 1993 Family and Medical Leave Act is 49 workers (United States Department of Labor 2002; n.d.). The European Commission and the United Kingdom categorize enterprises with fewer than 50 employees as small and those with less than 250 employees as medium-sized (European Commission 2005; United Kingdom Department for Business Enterprise and Regulatory Reform 2005). Smaller nations not surprisingly tend to maintain smaller maximum sizes for small business classifications. For example, the threshold for eligibility for government small business programs is 19 or fewer employees in Australia and New Zealand (New Zealand Ministry of Economic Development 2005; Australia Department of Industry Tourism and Resources 2007). Note that these are illustrative examples that do not cover the breadth of policies and definitions found in the United States or worldwide.

[116] These are the number of employees, both full-time and part-time, reported by each establishment as part of the *Census of Manufactures*. The exclusion of administrative records omits the very smallest stand-alone establishments, typically those with five or fewer employees.

[117] Two additional size categories were also tested (less than or equal to 500 and 100 employees), with results that generally follow the patterns detailed in this section.

[118] The data concerning the domination classifications are repeated from Table 6.1.

Table 8.6. Sample Descriptive Information for Absolute and Relative Size Classifications.

SIC	30			354			382		
Industry	rubber & plastics			metalworking machinery			measuring & controlling devices		
Year	1992	1997	2002	1992	1997	2002	1992	1997	2002
Sample observations	6,747	8,000	6,546	5,189	5,490	4,161	1,384	1,540	1,201
Mean employment	78	82	91	33	38	36	97	94	111
Small (250 or fewer employees)	6,351	7,474	6,081	5,110	5,397	4,101	1,271	1,422	1,088
Percent	94	93	93	98	98	99	92	92	91
Small (50 or fewer employees)	4,037	4,650	3,552	4,459	4,585	3,482	886	969	718
Percent	60	58	54	86	84	84	64	63	60
Small (15 or fewer employees)	1,415	1,688	1,099	2,717	2,603	1,921	362	376	299
Percent	21	21	17	52	47	46	26	24	25
Dominator establishments	645	833	901	427	497	505	167	212	202
Percent	9.6	10.4	13.8	8.2	9.1	12.1	12.1	13.8	16.8
Mean employment	286	280	273	148	154	123	410	359	409
Dominated establishments	3,061	3,701	2,487	2,686	2,886	1,846	658	687	505
Percent	45.4	46.3	38.0	51.8	52.6	44.4	47.5	44.6	42.0
Mean employment	23	24	26	13	15	15	21	23	23
Remainder of establishments	3,041	3,466	3,158	2,076	2,107	1,810	559	641	494
Percent	45.1	43.3	48.2	40.0	38.4	43.5	40.4	41.6	41.1
Mean employment	89	97	91	36	41	34	93	82	80

classification, as do some 60 percent of the rubber and plastics and measuring and controlling devices plants. Despite the fact that 15 employees is considerably smaller than most absolute size thresholds used in the United States, nearly half of the metalworking machinery plants and between a fifth and a quarter of the establishments in the other two study industry samples meet the criterion.

The absolute and relative size criteria demarcate separate partitions within the estimation samples. The average employment in plants belonging to dominator and dominated firms varies by industry, with the metalworking machinery establishments substantially smaller than their counterparts in the other two study industries. Although the tabulations are not presented in Table 8.6 due to confidentiality considerations, there are small establishments that are classified as dominators and there are also a few dominated plants within the largest absolute size categories in most of the samples. With four different size partitions, four measures of regional industrial dominance, and nine industry-year samples, the models estimated for this extension produce an enormous volume of results, most of which are not printed in the text proper (the full marginal effects are reported in Appendix 11, and the estimated model coefficients are available from the author). Tables 8.7, 8.8, and 8.9 summarize the marginal effects of regional industrial dominance, the five agglomeration economies, and the plant size dummies, obtained from the models that use the concentration ratio dominance measure.[119] The tables simplify the information by presenting only the signs and estimated significance ranges of the effects. As before, the analysis context is akin to a census rather than a random sample, and statistical significance is less important than the signs and magnitudes of the variables. Yet, because in this case the significances pertain to marginal effects, they coincide with magnitude, and serve as a normalized measure of the influence strength. The size partitions subdivide the estimation samples (while maintaining the complexity of the translog production function), so that conventional significance levels are more difficult to obtain than in the primary models. Therefore, Tables 8.7 through 8.9 report marginal effects that are significant at the 80 percent confidence level or greater. As a final caveat, the substantive conclusions reached within this section are based upon prevailing trends and patterns rather than unfailing rules. An examination of the coefficient estimates and marginal effects for each model permutation, especially including those adopting the alternative dominance measures (contained in

[119] The marginal effects are calculated with the other variables held at the means of each relative or absolute size category.

Appendix 11), will reveal exceptions. Nevertheless, there are interesting tendencies that permeate the mass of data and hold for the most part across models that use different measures of regional industrial dominance.

There are definite productivity advantages and disadvantages accompanying relative establishment size. As noted in section 7.3.4, plants that belong to dominated firms substantially underperform in terms of production, whereas establishments that are part of dominator firms enjoy a productivity advantage. The distinction is not as clear cut in terms of absolute size. Small rubber and plastics establishments are less productive, all else equal, when small is defined so as to include all plants up to 250 employees, but are more productive on average than other establishments when small is restricted to 15 or fewer workers. If the absolute size threshold is set at 100 employees, the overall productivity difference between small and large is insubstantial. The pattern does not hold exactly for the other two study industries, but the same general conclusion is supported: very small size is advantageous, but when defined more broadly, such as is common in policy definitions, small establishments are at a productivity disadvantage in comparison with the other plants in the industry. The smallest plants may have assets other than those measured in this analysis that create production advantages, such as links to parent firms, proprietary production processes, or differentiated products (i.e., they may more commonly function as specialized or boutique manufacturers rather than competitive mass producers).

Although both effects are highly significant, the impact of absolute size on production is typically much weaker than that of relative size. For example, in the 1992 rubber and plastics sample, small plants with 15 or fewer employees produce

Table 8.7. Significance of Marginal Impacts Including Plant Size Interactions for Rubber and Plastics (SIC 30).

		1992				1997				2002			
		Dom.	Sm.≤250	Sm.≤50	Sm.≤15	Dom.	Sm.≤250	Sm.≤50	Sm.≤15	Dom.	Sm.≤250	Sm.≤50	Sm.≤15
Dominators		+++				+++				+++			
Dominated / Small		–––	–––		+++	–––	–––		+++	–––	–––		+++
Dominance	dominator	++											
	neither / large	–––	+++			–––				–––	+++	+	+
	dominated / small				–								
Labor	dominator					––							
Pooling	neither / large				+++					+++		+	+
	dominated / small	+	++	+									
Manufactured	dominator												
Inputs	neither / large	+											
	dominated / small												
Producer	dominator												
Services	neither / large									++			+
	dominated / small										+		
Research	dominator									+			
	neither / large					+++					–		
	dominated / small							––	–				
Patents	dominator												
	neither / large	–					+++			+	+++	+	+
	dominated / small					+++				++			

Notes: A single plus or minus sign indicates significance at the 80 percent confidence level, a double sign 90 percent confidence level, and a triple sign 95 percent confidence level. Dom. refers to the model with two dummy variables for dominator and dominated plants. Sm. refers to the models with a single dummy variable for small plants. "Neither" and "dominated" label the dominance models, and "large" and "small" pertain to the small establishment models. The shaded cells are not required for the small establishment models.

Table 8.8. Significance of Marginal Impacts Including Plant Size Interactions for Metalworking Machinery (SIC 354).

		1992				1997				2002			
		Dom.	Sm.≤250	Sm.≤50	Sm.≤15	Dom.	Sm.≤250	Sm.≤50	Sm.≤15	Dom.	Sm.≤250	Sm.≤50	Sm.≤15
Dominators		+++				+++				+++			
Dominated / Small		−−−		−−−		−−−	−−−	−−−	+++	−−−	−	−−−	+++
Dominance	dominator									−			
	neither / large	−−−	+++	+		−−−				−−−			
	dominated / small	−−				−−−	−−−	−−−	−−−	−−	−	−	−−
Labor Pooling	dominator	+++				−−−				+			
	neither / large				+	−−−	−−−		−				
	dominated / small					−−−	−−−	−−	−−−				
Manufactured Inputs	dominator					++				−−			
	neither / large	+					+++			−−−			−−−
	dominated / small					+					−−−	−−−	−
Producer Services	dominator					−−				+++			
	neither / large					−	−−−			++			+++
	dominated / small		+	+		−−−			−−			+	
Research	dominator	−−								−			
	neither / large	−−−	−	−−−						−−	+	−	
	dominated / small	−−											
Patents	dominator	+++				+++				+++			
	neither / large	+++				+++		++	+++	+++		+++	+++
	dominated / small	+				+++	++	+		+++	+++	++	

Notes: A single plus or minus sign indicates significance at the 80 percent confidence level, a double sign 90 percent confidence level, and a triple sign 95 percent confidence level. Dom. refers to the model with two dummy variables for dominator and dominated plants. Sm. refers to the models with a single dummy variable for small plants. "Neither" and "dominated" label the dominance models, and "large" and "small" pertain to the small establishment models. The shaded cells are not required for the small establishment models.

Table 8.9. Significance of Marginal Impacts Including Plant Size Interactions for Measuring and Controlling Devices (SIC 382).

		1992				1997				2002			
		Dom.	Sm.≤250	Sm.≤50	Sm.≤15	Dom.	Sm.≤250	Sm.≤50	Sm.≤15	Dom.	Sm.≤250	Sm.≤50	Sm.≤15
Dominators		+++				+++				+++			
Dominated / Small		−−−		−−−	−−−	−−−	−−−		++	−−−	−		+
Dominance	dominator	−											
	neither / large	−−											
	dominated / small	−−−		−	−−	−−−			−−				
Labor	dominator									−			
Pooling	neither / large		+++										
	dominated / small		+++		+++		+	+					
Manufactured	dominator					+++							
Inputs	neither / large		−−−			+					−		−
	dominated / small		−								−	−	−
Producer	dominator					−−				−			
Services	neither / large		++										
	dominated / small												
Research	dominator												
	neither / large				++	+		++	++				
	dominated / small		++				++						
Patents	dominator									+++			
	neither / large			+		++	+	++			+		
	dominated / small				−	+							

Notes: A single plus or minus sign indicates significance at the 80 percent confidence level, a double sign 90 percent confidence level, and a triple sign 95 percent confidence level. Dom. refers to the model with two dummy variables for dominator and dominated plants. Sm. refers to the models with a single dummy variable for small plants. "Neither" and "dominated" label the dominance models, and "large" and "small" pertain to the small establishment models. The shaded cells are not required for the small establishment models.

approximately eight percent more output on average than other establishments. The output of establishments with up to 250 employees averages four percent less than larger plants. Dominator plants, on the other hand, produce nearly 14 percent greater output and dominated plants 19 percent less than establishments that are neither dominators nor dominated. Similar comparisons hold for the other industry-year pairs. In terms of overall output, the size status of a manufacturing plant relative to other regional establishments in the industry carries more influence than absolute size.

The influence of regional industrial dominance on production tends to be the most negative for those establishments in the rubber and plastics and the metalworking machinery industries that do not belong to either dominator nor dominated parent firms. In the measuring and controlling devices samples, dominated plants rather than those in the “neither dominator nor dominated” category are the most negatively affected by dominance. The marginal effects of regional industrial dominance are more clearly delineated by the relative than the absolute size classifications. This is as might be expected, since the conceptual framework in Chapter Three suggests that relative size defines interactions between regional establishments within the same industry. Small establishments are usually negatively affected by regional industrial dominance, or equivalently large establishments are positively influenced, but none of the size definitions tested produces a noticeably stronger demarcation of the conditioning effect of absolute size. Many of the calculated marginal effects for each of the three absolute different size partitions are small enough in magnitude that they fail to reach even the 80 percent confidence level plateau.

There are fewer patterns with respect to the agglomeration economy measures that hold across different study years and industries. Labor pooling possibilities, for example, seem to favor both large and small measuring and controlling devices establishments in 1992, but provide almost no productivity advantages for any size category within the industry in 1997 or 2002. The influence of labor pooling is almost uniformly negative in the metalworking machinery industry for subsets of establishments defined by both absolute and relative size classifications, but only for the 1997 model. Rubber and plastics plants that employ between 15 and 250 workers seem to benefit from locally available labor pools only in 1992. The two supply pooling variables exhibit inconsistent behavior with respect to establishment size as well. This finding is not very surprising given the ambiguous direction and insignificant magnitude of the calculated direct effects of these agglomeration economies on plant production.

The two measured types of knowledge spillovers demonstrate conditioning influences that fit better with the direct effects observed earlier (see section 7.3.5). In two of the three study years (1992 and 1997), measuring and controlling device manufacturers benefit from proximity to related academic research, particularly those of intermediate size: smaller than 250 but greater than 15 employees. Metalworking machinery plants tend to exhibit a negative influence on production from research, particularly with regard to the "neither dominator nor dominated" relative size classification. Patenting has a highly significant positive effect on productivity for metalworking machinery establishments in all three dominance classifications, and in 1997 and 2002 also benefits plants employing from 15 to 250 workers.

Overall, relative size is more appropriate than absolute size for indicating the way in which plant size conditions the influence of regional industrial dominance on production, but the evidence pertaining to the agglomeration economy variables is decidedly mixed. Most of the marginal effects of potential agglomeration advantages are insignificant, and those that are substantial do not obviously favor either the absolute or relative size classifications. None of the three definitions of "small" establishments outperforms the others in terms of revealing meaningful interactions between plant size and agglomeration influences, yet the differences observed between small and large plants certainly are not robust to the range of "small" considered in this extension.

Finally, it is worth noting that a thorough comparison of the plant size interaction terms involving regional industrial dominance or a particular agglomeration economy variable with the corresponding marginal effects on the different size categories (both contained in Appendix 11) demonstrates that the patterns, defined by either magnitude or significance, do not match. In other words, the plant size classifications that evidence substantial effects on productivity from either regional industrial dominance or potential agglomeration advantages are not necessarily those for which there are significant interaction terms between the size classification dummy variable and the measure of regional industrial dominance or agglomeration. The implication is that the substantial differences among plant size groups illustrated in Tables 8.7 through 8.9 may arise more from divergences between category means than the interaction coefficients themselves. The ways in which small and large plants exhibit distinct productivity behavior may be intrinsically related to their size and production technology and not pertain specifically to the influences of environmental influences such as dominance and agglomeration.

CHAPTER NINE: SUMMARY AND IMPLICATIONS

9.1. Study Summary and Principal Findings

This study examines the relationship between regional industrial dominance and economic performance by focusing on the productivity of individual establishments. A production function system is estimated for cross-sectional samples using confidential nationwide establishment-level data. The nine cross-sections represent three contrasting manufacturing industries and three years that span a 15-year time period. Measures of regional industrial dominance and five types of potential localized agglomeration economies, four of which are modeled as attenuating in influence with increasing distance from each plant's location, are included in the estimation system along with controls for various regional characteristics.

Two primary research hypotheses guide the analysis. The first is that manufacturing plants located in regions in which their industries are dominated by a single or a few relatively large companies are less productive than establishments in the same industries that are located in regions exhibiting a broader distribution of firm sizes. The empirical results uphold this contention. Regional industrial dominance is a large negative influence on production for all three of the studied manufacturing industries, particularly for establishments belonging to companies small enough to be dominated within their regional industry.[120] The effect of dominance is due to current rather than historic dominance conditions, though there are indications that high levels of dominance may lead to lower productivity in the future.

The second hypothesis posits that small establishments in regionally dominated industries have reduced productivity because they are less able to exploit external economies available in the regional environment in order to boost production and maximize their capacity to adapt to shifting local economic conditions. The research largely denies this hypothesis, finding few strong relationships between regional industrial dominance and potential agglomeration economies. In six out of nine industry-year samples, the estimated interactions between dominance and agglomeration are essentially inconsequential. The interpretation is that regional industrial dominance does not prevent firms from benefiting from localized agglomeration economies, and the lower productivity estimated for plants in regionally dominated industries is not the result of an inability to take advantage of agglomeration economies. Because other explanations are possible, the second research hypothesis cannot be definitively rejected. The direct impacts of the three labor and supply pooling agglomeration variables are themselves estimated to be small and inconsistent, so that it is not surprising that their interactions with regional industrial dominance are relatively weak. The agglomeration variables may lack sufficient construct validity to reveal subtle effects or may be weakened by the exclusion of plants in regional industries with relatively few firms (necessary for the regional industrial dominance concept to be meaningful). Regional industrial dominance may interact with different sources of external economies than those measured in this

[120] Regional industrial inequality, as indicated by the Gini coefficient, positively affects productivity, but its influence is substantially diminished for small plants.

analysis. Still, the conclusion most consistent with the model outcomes is that regional industrial dominance hampers productivity in small plants by means other than limiting the ability of small plants to benefit from localized agglomeration economies.

Three extensions to the main modeling analysis yield further detail while corroborating the main findings of the study. Estimates obtained by changing the pattern of spatial decay imposed on the labor pooling, supply pooling, and academic research variables suggest that labor pools and spillovers from academic research confer production advantages at relatively broad spatial scales. The productivity impacts of supply pooling remain slight across various spatial scales; high colinearity disrupts the estimation of the two supply pooling variables. Regional dominance measured across the entire private sector economy influences productivity at the establishment level, but does so independently of industry-specific regional dominance, signifying the need for a separate analysis of the phenomenon. Dominated plants underproduce and dominator plants produce more than the average establishment. Considering absolute size, the very smallest establishments, those with 15 or fewer workers, tend to be more productive than larger manufacturers, but if the term "small" is defined to encompass establishments as large as 100 or 250 employees, as is common in policy applications, then small plants are less productive. Relative size relates more closely than absolute size to the productivity effects of regional industrial dominance, whereas neither absolute nor relative size presents a consistently clearer delineation among establishments in terms of considering agglomeration effects. The differences among plants of various sizes appear to be more the result of divergent category sample means than interactions between plant size and environmental characteristics, suggesting that differences in production are intrinsic rather than determined by external factors. The conclusions stated above in respect to the two main research questions are robust to alternative spatial specifications of the agglomeration variables, the inclusion of regional economy-wide dominance measures, and partition by different plant size categories.

It is worth considering briefly the issue of causality in light of the primary conclusions reached in this analysis. The cross-sectional regression methodology yields evidence of substantial association between regional industrial dominance and establishment productivity, but cannot directly specify causation. Is it possible that instead of dominance reducing the productivity of small businesses in the regional industry, regional industrial dominance itself arises as an outcome of inferior business performance, perhaps via relatively high failure or merger rates for small and medium-sized firms? Although such a reversal of the assumed causal direction of the relationship may be feasible theoretically, it is not plausible. The production function in this study is specifically designed to include the regional environmental factors, including specific sources of agglomeration economies, that might lead to differential failure rates (see section 4.7). Mergers and acquisitions do not follow from substandard productivity. If the causal direction ran from productivity to dominance, productivity should be substantially correlated with decreases in regional industrial dominance over time. In most of the models, however, the estimated coefficients of the historic dominance variable are negligibly small. Moreover, the structure of the regional industrial dominance phenomenon itself makes the proposition highly improbable. Dominance develops over long periods of time.[121] Even if dominance were caused by relatively poor

[121] This would be the case especially if regional industrial dominance resulted from differential firm failure rates.

production among small establishments, contemporary productivity differences across regions would not necessarily relate to the levels of regional industrial dominance observed concurrently. Given the high degree of skewness of the firm size distribution in most regional industries, the considerable differences in the level of industrial dominance observed across regions are very unlikely to result from the differential survival probabilities of small and medium-sized businesses alone. It is reasonable to conclude that it is regional industrial dominance that negatively influences small business productivity.

9.2. Research Contributions

This dissertation extends previous research in a number of ways. First and foremost is the close examination of regional industrial dominance, a topic that has not been investigated before in systematic fashion. The subject of regional industrial dominance points attention toward issues of industrial organization at the regional scale, the effects of industrial structure on production, and the manner in which the successes and failures of individual plants combine to determine regional economic performance. The estimation results demonstrate the importance of regional industrial dominance in shaping establishment productivity, highlight the linkage between the regional environment and economic performance at the firm level, and encourage further research on the subject of dominance and its possible linkages with other characteristics of regions and establishments.

Chapters Six through Eight provide a baseline analysis of regional industrial dominance that covers three industries across the contiguous United States and enlarges the body of research modeling productivity at the level of individual plants. The modeling procedures incorporate several advances from earlier methods. By drawing on the plant-level data contained in the *Longitudinal Research Database*, the statistical framework bypasses many of the econometric concerns and issues of inadequate or incomplete information that plague earlier production function estimations. The agglomeration variables indicate specific sources of potential agglomeration economies rather than acting as broad proxies, and measure the spatial dimension of interfirm relationships in a continuous rather than regionally aggregate fashion. The flexible translog form permits a wide variety of functional properties to be tested within the modeling framework: homotheticity, homogeneity, constant returns to scale, the Hicks-neutrality of regional industrial dominance and agglomeration economies, and the reduction to the Cobb-Douglas and CES functional forms. The fact that these simplifying properties that are commonly assumed *a priori* are rejected empirically in this analysis validates the selection of the more accommodating translog specification.

The analysis connects two separate threads of investigation contained within distinct fields of research. Concepts and theoretical background are drawn from previous work on both firm size distributions and agglomeration economies. While not the first attempt to analyze industrial structure and regional economic characteristics simultaneously (e.g., Feser 2002; Rosenthal and Strange 2003; Renski 2006), this study focuses directly on the intersection of the two areas and substantially extends the approach.

9.3. Implications for Regional Development Policy

The results of this analysis yield new perspectives and also raise questions for economic developers and others responsible for directing regional development policy. The primary conclusion is that regional industrial structure matters in determining the efficiency of local manufacturers. Small businesses are less productive when their industry is dominated within the regional economy by a single or small group of manufacturers. As mentioned above, this study does not successfully ascertain the exact manner in which the relationship between regional dominance and productivity unfolds. The estimation results indicate relatively little interaction between dominance and agglomeration, leading to the conclusion that regional industrial dominance does not hinder productivity by preventing manufacturing plants from taking advantage of regional agglomeration economies.

The outcome is unfortunate for the practice of economic development. A clearer understanding of the mechanism by which dominance relates to establishment-level productivity is needed to design and predict the effects of regional policies. Without this knowledge, the success of policies intended to help small businesses take advantage of regional agglomeration possibilities or to provide accessible substitutes may be expected to vary with the setting or to fluctuate over time, or such efforts might be ineffective in general. Moreover, dominance is a phenomenon that by its nature is likely to endure over time and is difficult to alter with the policy tools available at the local and regional levels. Additional research that aims to detail the means by which dominance influences economic performance will aid the design of policy instruments to counter the negative effects of regional industrial dominance.

Nevertheless, simply understanding that regional industrial dominance is an issue that affects economic performance may engender creativity, both in designing policies to counter the influence of dominance and in shaping policies to work within local economic conditions. This study reinforces the notion that regional industrial structure, both industry-specific and economy-wide, is an important characteristic of a regional economy. It is to the advantage of regional economic analysts and economic development practitioners that currently examine overall regional concentration, and sometimes industrial concentration at the national level, to pay attention to concentration and dominance at the level of regional industries. Both analysts and policymakers should note the distinction between relative and absolute size, and the sensitivity of economic performance to the particular definition of small business. Locally dominated firms are particularly vulnerable to the influence of regional industrial dominance and thus may require extra support. The benefits of potential agglomeration economies shift substantially across different absolute size categories of establishments, so that inappropriate policy definitions may cause economic development programs to be unfaithful to their intentions.

The study suggests that regional industrial dominance restricts economic adaptability, despite the uncertainty of the pathway by which dominance influences establishment output. Although the idea that dominance directly inhibits individual firms from allocating internal and external resources efficiently receives little empirical support, it is apparent that regional industrial dominance is associated with diminished small business productivity. The growth and dynamism of small businesses are argued to be crucial elements of regional adjustment capacity. To the extent that regional industrial dominance hinders the productivity and expansion of fledgling businesses, and perhaps local innovation and entrepreneurial activity as well, the local economy possesses less flexibility to react to changing economic conditions. Restructuring in the face of a major technological advance or economic upheaval may prove impossible. The goal of developing effective policies to address the issues that arise from disadvantageous regional industrial structures should provide further impetus for conducting research on the question of how regional industrial dominance acts to influence economic performance.

Finally, the results pertaining to the effects of agglomeration economies provide information directly useful to economic development policymakers. Locational factors that affect economic performance are more susceptible to policy influence than are firm-specific traits (Hoogstra and van Dijk 2004). Although potential labor and supply pools seem to have little effect on manufacturing output, spillovers of knowledge and information from private sector innovative activity do benefit production. Academic research in relevant fields improves the productivity of measuring and controlling device establishments, and may have a similar influence for other technology-intensive industries. Programs that support private research, ranging from technology grants and research and development tax subsidies to developing networks among regional knowledge producers and manufacturers, may boost regional productivity and enhance competitive advantage. It may be more effective to assist research efforts than to attempt to establish or mediate local supplier-purchaser relationships. The broad spatial scales at which these knowledge externalities operate mean that establishments need not rely solely on local knowledge producers. Policymakers may find it to be more cost-effective to concentrate public research efforts at large laboratories or universities that are only near enough to manufacturers to sustain occasional contact, and to connect peripheral districts with more centrally located areas (Phelps *et al.* 2001). In general, agglomeration advantages are more likely to benefit economic development efforts if encouraged and promoted at the regional rather than local or municipal levels (Scott and Storper 2003). Extending the scope of the current analysis to cover additional industries will provide further guidance to policymakers along these lines.

9.4. Future Research Directions

There are several directions in which the research in this study can be extended or refined. Although the particular industries are selected carefully with the goal of providing optimal contrast (see section 5.3), the results ultimately are based on information that pertains to only a small subset of private sector establishments, all classified within the manufacturing sector. Expanding the analysis of regional industrial dominance to other manufacturing industries, and, with suitable modifications in terms of data sources and constructs, to other economic sectors as well, would enhance the generalizability of the inferences that can be made. Adding time periods would also increase external validity, and modifying the methodology from strictly cross-sectional to an approach suitable for a short time series might enhance the depth of information gained as well as test the sensitivity of the conclusions to the particular mode of statistical analysis. The brief examination of economy-wide dominance contained in section 8.3 indicates that a full quantitative analysis combining both intra- and inter-industry dominance may be enlightening. As mentioned in Chapter Three, economic performance may be investigated with regard to outcomes other than productivity, such as innovation, business survival, or entrepreneurial activity. It would be interesting to compare the influence of regional industrial dominance within the United States with the experiences of establishments located in other nations.

In light of the generally disappointing performance of the agglomeration economy variables, developing and incorporating additional externality indicators either would corroborate the denial of the second research hypothesis or perhaps would succeed in identifying the more elusive sources of agglomeration economies that translate the influence of regional industrial dominance into negative effects on small business performance. These might include knowledge spillovers originating from government and private research laboratories, customer or market demand pooling, and capital financing availability. Locating supplementary sources of data adequate for implementation with the current approach is a prerequisite that may prove difficult to meet, and variable colinearity is likely to be problematic. Perhaps the most important constraint is the restricted degree of variation in potential agglomeration within the plant samples, a limitation exacerbated by the imposition of a minimum regional industry scale to support the notion of regional industrial dominance.[122] The agglomeration economy measures may be modeled with different or more complex decay functions or at a finer spatial grain (specifying locations and distances more precisely than by county centroids). The weakness and inconsistency of the agglomeration variable coefficients estimated in this analysis imply, however, that the returns to conducting such an exercise are not likely to be commensurate with the additional effort required.

[122] Additional possible sources of agglomeration economies are factors that can be emphasized in qualitative case studies (see footnote 11 in Chapter Two).

More general investigation of the processes and implications of regional industrial dominance is in order as well. This study does not confirm the hypothesis that the negative association of dominance with the production of small establishments arises from constraints on the exploitation of potentially beneficial local agglomeration economies. Therefore, the question remains: by what mechanism or mechanisms does regional industrial dominance influence economic performance? Examining connections such as the inter- and intrafirm relationships among establishments, the interactions between small and large firms within a regional industry, and the aggregation of individual establishment characteristics into regional industrial structures may lead to an explanation. These topics have been and continue to be the subject of research in industrial organization and business, as well as regional science and economic development; adding the concept and perspective of regional industrial dominance to the mix may elicit new insights and innovative directions.

APPENDICES

Appendix 1. Derivation of Factor Share Equations and Production System

Let the production function be expressed as in equation (4.8):

(A1.1) $$Q = g(Z) \cdot f(X)$$

where Q is plant output, X is a vector of conventional inputs, and Z is a vector of other relevant regional characteristics. The establishment then seeks to maximize the profit function

(A1.2) $$\Pi = \frac{\partial C}{\partial Q} Q - \sum_i P_i X_i$$

where Π is total profits, $\partial C / \partial Q$ is the marginal cost of output, and P_i is the input price of the i^th input X_i. Given that the production function satisfies the typical regularity conditions (see section 4.6), and that input markets are competitive, the first-order condition for profit maximization states that

(A1.3) $$\frac{\partial \Pi}{\partial X_i} = \frac{\partial C}{\partial Q} \cdot \frac{\partial Q}{\partial X_i} - P_i = 0$$

for each input X_i, and, rearranging,

(A1.4) $$\frac{\partial Q}{\partial X_i} = \frac{P_i}{\partial C / \partial Q} = \lambda P_i$$

where λ is a Lagrange multiplier that is the reciprocal of the marginal cost of output. Since the relation expressed in equation (A1.4) holds for each input, both sides may be multiplied by the quantity of the i^th input, X_i, and summed over the inputs to yield a multiple of the total input cost C:

(A1.5) $$\sum_i \frac{\partial Q}{\partial X_i} X_i = \lambda \sum_i X_i P_i = \lambda C .$$

Rearranging equation (A1.5) to isolate λ and substituting into equation (A1.4) yields

$$\frac{\partial Q}{\partial X_i} = \frac{\sum_i (\partial Q/\partial X_i) X_i}{C} P_i$$

or, rearranging again,

$$P_i = C \frac{\partial Q/\partial X_i}{\sum_i (\partial Q/\partial X_i) X_i}. \tag{A1.6}$$

Equation (A1.6) is the inverse input demand function, representing the unit input price that results in the particular input demand X_i associated with total output Q and total cost C. It can be rewritten in terms of logarithmic input and outputs as

$$P_i = C \frac{(\partial \ln Q/\partial \ln X_i)(Q/X_i)}{\sum_i (\partial \ln Q/\partial \ln X_i)(Q/X_i) X_i} = C \frac{\partial \ln Q/\partial \ln X_i}{\sum_i (\partial \ln Q/\partial \ln X_i) X_i}. \tag{A1.7}$$

Finally, by rearranging once again, an equation for the cost share, S_i, for the i[th] input, is obtained:

$$S_i \equiv \frac{P_i X_i}{C} = \frac{\partial \ln Q/\partial \ln X_i}{\sum_i (\partial \ln Q/\partial \ln X_i)}. \tag{A1.8}$$

Reprinting equation (4.9), the translog form of the production function is:

$$\begin{aligned} \ln Q = \alpha_0 &+ \sum_i \alpha_i \ln X_i + \frac{1}{2} \sum_i \sum_j \beta_{ij} (\ln X_i \ln X_j) \\ &+ \sum_k \gamma_k \ln Z_k + \sum_i \sum_k \mathrm{I}(i,k) \lambda_{ik} \ln X_i \ln Z_k + \sum_k \sum_l \mathrm{I}(k,l) \lambda_{kl} \ln Z_k \ln Z_l \end{aligned}. \tag{A1.9}$$

The logarithmic marginal products of each input are obtained by differentiating (A1.9) with respect to X_i:

$$\begin{aligned} \frac{\partial \ln Q}{\partial \ln X_i} &= \alpha_i + \frac{1}{2} \sum_j \beta_{ij} \ln X_j + \frac{1}{2} \sum_j \beta_{ji} \ln X_j + \sum_k \mathrm{I}(i,k) \lambda_{ik} \ln Z_k \\ &= \alpha_i + \sum_j \beta_{ij} \ln X_j + \sum_k \mathrm{I}(i,k) \lambda_{ik} \ln Z_k \end{aligned}. \tag{A1.10}$$

Substituting (A1.10) into the formula (A1.8), the cost shares, S_i, for the translog production function are expressed as:

$$\text{(A1.11)} \qquad S_i = \frac{\partial \ln Q / \partial \ln X_i}{\sum_i \left(\partial \ln Q / \partial \ln X_i \right)} = \frac{\alpha_i + \sum_j \beta_{ij} (\ln X_j) + \sum_k I(i,k) \lambda_{ik} \ln Z_k}{\sum_i \left(\alpha_i + \sum_j \beta_{ij} (\ln X_j) + \sum_k I(i,k) \lambda_{ik} \ln Z_k \right)},$$

which is equivalent to equation (4.10) in the text.

The only assumptions required for this derivation are the production function regularity conditions, establishment-level profit maximization, and competitive input markets. This differs from many production function studies that use factor demand functions derived directly from the (logarithmic marginal) production or cost function using Shephard's lemma (Chung 1994; Lall *et al.* 2001). Such factor demand functions are, under the assumptions of constant returns to scale and Hicks-neutral technical change, equivalent to the cost share functions derived here. In contrast, this derivation, first outlined by Kim (1992), derives the cost shares from the (inverse) input demand functions and first-order profit maximization conditions and thus does not require assuming constant returns to scale or Hicks-neutral technical change.

Appendix 2. Calculation of Monotonicity and Convexity Regularity Criteria

The marginal product of input X_i, derived by differentiating equation (3.9), is

(A2.1)
$$\frac{\partial Q}{\partial X_i} = \frac{Q}{X_i}\left(\alpha_i + \sum_j \beta_{ij} \ln X_j + \sum_k \lambda_{ik} \ln Z_k\right).$$

The second-order derivatives are

(A2.2)

$$\frac{\partial^2 Q}{\partial X_i^2} = \frac{Q}{X_i^2}\left(\beta_{ii} + \left(\alpha_i + \sum_j \beta_{ij} \ln X_j + \sum_k \lambda_{ik} \ln Z_k\right)\left(\alpha_i + \sum_j \beta_{ij} \ln X_j + \sum_k \lambda_{ik} \ln Z_k - 1\right)\right)$$

and

(A2.3)

$$\frac{\partial^2 Q}{\partial X_i \partial X_j} = \frac{Q}{X_i X_j}\left(\beta_{ij} + \left(\alpha_i + \sum_j \beta_{ij} \ln X_j + \sum_k \lambda_{ik} \ln Z_k\right)\left(\alpha_j + \sum_i \beta_{ij} \ln X_i + \sum_k \lambda_{jk} \ln Z_k\right)\right)$$

for $i \neq j$. The bordered Hessian matrix is

$$\mathbf{H} = \begin{bmatrix} 0 & \frac{\partial Q}{\partial X_1} & \frac{\partial Q}{\partial X_2} & \frac{\partial Q}{\partial X_3} & \frac{\partial Q}{\partial X_4} \\ \frac{\partial Q}{\partial X_1} & \frac{\partial^2 Q}{\partial X_1^2} & \frac{\partial^2 Q}{\partial X_1 \partial X_2} & \frac{\partial^2 Q}{\partial X_1 \partial X_3} & \frac{\partial^2 Q}{\partial X_1 \partial X_4} \\ \frac{\partial Q}{\partial X_2} & \frac{\partial^2 Q}{\partial X_1 \partial X_2} & \frac{\partial^2 Q}{\partial X_2^2} & \frac{\partial^2 Q}{\partial X_2 \partial X_3} & \frac{\partial^2 Q}{\partial X_2 \partial X_4} \\ \frac{\partial Q}{\partial X_3} & \frac{\partial^2 Q}{\partial X_1 \partial X_3} & \frac{\partial^2 Q}{\partial X_2 \partial X_3} & \frac{\partial^2 Q}{\partial X_3^2} & \frac{\partial^2 Q}{\partial X_3 \partial X_4} \\ \frac{\partial Q}{\partial X_4} & \frac{\partial^2 Q}{\partial X_1 \partial X_4} & \frac{\partial^2 Q}{\partial X_2 \partial X_4} & \frac{\partial^2 Q}{\partial X_3 \partial X_4} & \frac{\partial^2 Q}{\partial X_4^2} \end{bmatrix}$$

for four standard inputs into production. The Hessian matrix **H** is negative semidefinite if each principal minor alternates in sign or is zero, with the smallest (two-by-two) principal minor being negative or zero.

Appendix 3. 1990 Labor Market Areas

Figure A.3.1 displays the 1990 Labor Market Areas for the continental United States. For the details of their construction and the individual county components, see United States Department of Agriculture (2003).

Figure A.3.1. 1990 Labor Market Areas.

Appendix 4. Occupational Data for Labor Pooling

The occupational data for the labor pooling variable come from the *National Staffing Patterns* matrices (United States Bureau of Labor Statistics n.d.-b). These matrices provide estimates of employment by occupation constructed from survey responses for industries at the national level. The 1997 and 2002 matrices are used to calculate the labor pooling variable for 1997 and 2002. Prior to 1996 industries were surveyed on a rotating basis once every three years, but since manufacturing was surveyed in 1992, the 1992 staffing patterns are applicable for constructing the 1992 version of the labor pooling variable.

The staffing patterns data are classified into industries by three-digit SIC codes for 1992 and 1997. The 2002 staffing patterns matrix uses NAICS codes but at the four-digit level of disaggregation, so the crosswalk in Table 5.1 cannot be applied directly. Table A.4.1 approximates the crosswalk from Table 5.1 for the level of four-digit NAICS codes.

Occupational codes present a trickier translation issue. The 1992 and 1997 staffing patterns data use Occupational Employment Statistics (OES) codes, and the 2002 matrix employs Standard Occupational Codes (SOC). The Census Bureau uses its own occupational coding structure in the *Equal Employment Opportunity* tabulations,

Table A.4.1. Study Industry Definitions by SIC and Four-Digit NAICS Codes.

Industry	SIC	NAICS
rubber and plastics	30	3261 3262
metalworking machinery	354	3335
measuring and controlling devices	382	3345

however, and the classification system was updated between the 1990 and 2000 censuses. Thus combining the staffing patterns with the Census occupational data requires three crosswalks: OES to 1990 Census, OES to 2000 Census, and SOC to 2000 Census. These translations are created with the help of occupational descriptions from the Bureau of Labor Statistics and the Census Bureau but rely substantially on the judgment of the author. Because they are long, the crosswalks are not printed here, but are available from the author. The output is arranged according to the Census codes.

The OES and SOC codes do not match the Census occupational codes from either census year on a one-to-one basis. The crosswalks include numerous instances both of single OES or SOC codes mapping to multiple Census codes and multiple OES or SOC codes mapping into a single Census code. Since the combined data are expressed in Census occupational codes, the one-to-many relationship from OES or SOC to Census coding is not of concern, but the many-to-one mapping from several OES or SOC codes to a single Census occupational code creates an ambiguity in determining how to apportion the Census occupational employment. The procedure used is to map the OES and SOC codes to the Census occupational code in proportion to the amount of employment in that occupation for each study industry.

Table A.4.2 displays the total number of Census occupational codes and the approximate percentage of total employment in the study industries represented by the top 15 occupations for each of the study years. Because the 1990 Census classification system contains fewer occupational codes than the 2000 system, the top 15 occupations might be expected to represent a larger fraction of the total employment in the study industries in 1992. This supposition holds true comparing 1992 and 1997, but the largest

Table A.4.2. Census Occupational Codes and Study Industry Employment.

Year	Number of Census Occupational Codes	Range of Percent of Employment in Top 15 Occupations for Study Industries (SICs 30, 354, 382)
1992	253 (1990 Census)	48-52
1997	279 (2000 Census)	44-51
2002	279 (2000 Census)	50-61

percentage accounted for by the top 15 occupations occurs in 2002, perhaps because employment in the study industries is increasingly concentrating over time in occupations that are not as highly disaggregated by the classification scheme.

Appendix 5. SIC and Input-Output Codes for Supply Pooling

The *Benchmark Input-Output Accounts of the United States* are used to calculate the percent of manufacturing and producer services inputs that each of the three study industries purchases from each supplier industry on a nationwide basis (United States Bureau of Economic Analysis n.d.). The Bureau of Economic Analysis prepares the *Accounts* from data collected every five years as part of the Economic Census, in the same years as the *Census of Manufactures*. The *Accounts* classifies industries by Input-Output (IO) codes, a system that is not identical to the SIC or the NAICS but corresponds closely, particularly within the manufacturing sector (for which the IO codes are more disaggregated than in most other sectors). In addition, the IO coding system was updated between 1992 and 1997. The 2002 *Accounts* were not available at the time of writing, so the purchasing amounts from 1997 are applied to both the 1997 and 2002 study years.

In order to examine interindustry relationships, the Make and Use tables of the *Accounts* are first transformed into an interindustry transactions matrix. The Use table (**U**) contains the dollar amount of each commodity used by each industry; the Make (**M**) table contains the dollar amount of each commodity produced by each industry. The transactions matrix (**T**), which presents the dollar value of sales made by each (row) industry to each (column) industry, is constructed from the Make and Use tables as

(A5.1) $$\mathbf{T} = \left(\mathbf{M} \cdot diag(\mathbf{O})^{-1}\right) \cdot \mathbf{U}$$

where **O** is a vector of total commodity output, calculated by summing the columns of the Make table (or the rows of the Use table). After eliminating commodities not produced domestically by private industry, such as government services, household production, and imports, the 1992 tables have 491 industries and 479 commodities, and the 1997 versions include 511 industries and 512 commodities.

Table A.5.1 displays the 1992 and 1997 IO codes linked to each of the study industries. Table A.5.2 lists the IO codes classified as manufacturing input and producer service suppliers.

Table A.5.1. Input-Output Codes for Study Industries.

Industry	SIC	1992 IO	1997 IO	
rubber and plastics	30	320100	326110	3261A0
		320200	326120	326210
		320300	326130	326220
		320400	326160	326290
		320500	326192	339991
		320600	32619A	
metalworking machinery	354	470100	332997	333515
		470200	333511	33351A
		470300	333512	333991
		470401	333513	333992
		470402	333514	
		470404		
		470405		
		470500		
measuring and controlling devices	382	620102	333314	334515
		620200	334512	334516
		620300	334513	33451A
		621000	334514	339111
		621100	334515	

Table A.5.2. Input-Output Codes for Manufacturing and Producer Services.

Industry Sector	1992 IO	1997 IO
manufacturing	130100 through 641200	113300 311111 through 33451A 334612 through 339115 339910 through 33999A 511110 through 5111A0 512200
producer services	650701 670000 700100 through 700500 710201 730102 through 730303	334611 48A000 511200 513100 514100 through 531000 532400 532A00 541100 through 541920 5419A0 through 561400 561600 through 561900

Appendix 6. Patents and Technology Classes

Table A.6.1 displays the list of industries cited in at least five percent of the target industry's patents along with the citation frequency from the technology flow matrix developed by Koo (2005a). Table A.6.2 lists the patent technology classes relevant to the study industries and the industries cited by the study industries' patents (modified from United States Patent and Trademark Office 2004).

Table A.6.1. Industries Cited in Patents and Relative Importance (Citation Frequency).

Industry	SIC	Cited Industries (Relevance Weight)	
rubber and plastics	30	30	(.3061)
		34	(.1088)
		282	(.0631)
		38	(.0628)
		32	(.0563)
metalworking machinery	354	354	(.4880)
		34	(.0845)
		355	(.0831)
		38	(.0578)
measuring and controlling devices	382	38	(.6935)
		367	(.0564)

Table A.6.2. Patent Technology Classes.

SIC	Patent Technology Classes									
282	008	106	428	502	508	520	521	523	525	526
	528	976								
30	002	004	005	008	012	015	016	024	029	036
	040	047	049	052	059	062	081	106	108	114
	116	119	126	128	135	137	138	150	152	156
	160	165	168	181	188	204	205	206	215	220
	221	223	224	229	238	239	242	248	251	256
	264	267	280	285	294	301	383	384	403	411
	416	422	427	428	429	441	474	482	492	521
	523	524	525	527	604	968				

Table A.6.2. Patent Technology Classes, continued.

SIC	Patent Technology Classes								
32	004	008	015	029	040	047	051	052	065	106
	110	119	126	131	138	156	166	174	181	188
	205	215	220	222	238	239	242	251	256	264
	267	277	285	335	349	359	405	411	422	427
	428	451	454	501	502	523	524	968	976	
34	002	004	005	007	014	015	016	024	028	029
	030	037	038	040	043	047	049	052	054	056
	059	062	069	070	072	075	076	079	081	099
	104	105	109	110	111	114	116	119	122	125
	126	131	134	135	137	138	140	141	144	148
	156	160	165	166	168	172	180	181	182	185
	186	188	193	204	205	206	211	215	220	221
	222	223	224	232	237	238	239	242	244	245
	246	248	249	250	251	254	256	258	261	267
	269	280	285	289	292	293	294	295	296	297
	300	301	310	312	359	376	403	404	405	407
	410	411	413	414	416	419	427	428	431	441
	454	464	474	482	492	968	976			
354	029	030	059	072	073	074	076	081	082	083
	108	116	134	140	157	163	164	173	204	219
	221	226	228	239	242	249	254	266	269	279
	307	335	356	388	408	409	413	414	427	451
	470	483	492	505	901	968				
355	012	019	026	028	029	030	034	040	055	057
	062	065	066	068	069	074	079	083	087	096
	099	100	101	112	117	125	127	131	134	139
	141	142	144	147	156	157	159	162	164	181
	196	199	202	204	205	206	209	223	225	226
	241	242	249	254	261	264	270	271	276	289
	300	312	376	407	408	412	414	422	425	427
	428	451	452	492	493	505	526	968	976	

Table A.6.2. Patent Technology Classes, continued.

SIC	Patent Technology Classes								
367	029	049	052	073	083	116	117	118	125	134
	136	148	156	160	165	174	178	181	187	204
	205	206.	211	216	219	221	228	236	241	242
	244	246	250	257	264	307	313	314	315	326
	327	329	330	331	332	333	334	335	336	338
	340	341	342	343	345	348	349	358	359	360
	361	362	365	367	369	370	372	375	377	379
	380	381	385	386	414	427	428	429	434	438
	439	445	455	505	700	704	706	714	725	
38	002	004	005	015	027	029	033	034	036	040
	044	052	062	065	073	074	083	091	099	100
	110	116	122	126	128	134	135	136	137	144
	156	165	166	169	178	180	181	182	184	188
	202	203	204	205	206	210	215	219	221	222
	226	227	228	234	235	236	237	239	242	246
	249	250	252	264	266	269	271	280	294	297
	312	318	322	330	335	337	340	342	346	348
	349	351	352	353	355	356	359	361	362	367
	368	369	372	374	376	377	379	381	385	396
	399	408	414	416	417	422	427	428	430	431
	432	433	434	435	436	439	441	451	492	494
	505	523	526	528	600	602	604	606	607	623
	700	701	702	706	968	976				

Appendix 7. Heteroskedasticity-Corrected Versions of Primary Model Results

Tables A.7.1, A.7.2, and A.7.3 contain the model results with regional industrial dominance measured as a concentration ratio and with heteroskedasticity-corrected standard errors. The three tables correspond to tables 7.2, 7.3, and 7.4 in the main body of the text.

Table A.7.1. Parameter Estimates for Rubber and Plastics (SIC 30) with Heteroskedasticity-Corrected Standard Errors.

Year	1992				1997				2002			
Variable	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
α_0	8.2778	0.0127	652.56	0.00	8.4360	0.0120	704.22	0.00	8.7876	0.0149	588.84	0.00
α_k	0.1296	0.0022	59.58	0.00	0.1676	0.0021	80.62	0.00	0.1976	0.0026	74.72	0.00
α_l	0.3338	0.0026	129.91	0.00	0.3084	0.0021	148.22	0.00	0.2976	0.0034	87.43	0.00
α_e	0.0272	0.0033	8.35	0.00	0.0226	0.0031	7.22	0.00	0.0220	0.0036	6.18	0.00
α_m	0.4469	0.0031	142.24	0.00	0.4430	0.0028	157.74	0.00	0.4182	0.0036	116.70	0.00
β_{kk}	0.0854	0.0038	22.57	0.00	0.0965	0.0052	18.62	0.00	0.1020	0.0134	7.59	0.00
β_{ll}	0.1421	0.0033	43.34	0.00	0.1380	0.0025	54.41	0.00	0.1188	0.0047	25.08	0.00
β_{ee}	0.0190	0.0052	3.68	0.00	0.0167	0.0045	3.70	0.00	0.0160	0.0059	2.72	0.01
β_{mm}	0.1715	0.0039	44.45	0.00	0.1788	0.0039	46.24	0.00	0.1567	0.0104	15.13	0.00
β_{kl}	-0.0317	0.0025	-12.70	0.00	-0.0329	0.0027	-12.15	0.00	-0.0381	0.0074	-5.16	0.00
β_{ke}	-0.0026	0.0032	-0.80	0.43	-0.0022	0.0035	-0.65	0.52	-0.0035	0.0062	-0.57	0.57
β_{km}	-0.0564	0.0032	-17.79	0.00	-0.0666	0.0029	-22.69	0.00	-0.0731	0.0064	-11.37	0.00
β_{le}	-0.0050	0.0032	-1.54	0.12	-0.0048	0.0027	-1.78	0.08	-0.0030	0.0051	-0.60	0.55
β_{lm}	-0.1142	0.0027	-41.73	0.00	-0.1081	0.0022	-49.99	0.00	-0.0941	0.0062	-15.07	0.00
β_{em}	-0.0123	0.0035	-3.55	0.00	-0.0104	0.0030	-3.43	0.00	-0.0110	0.0048	-2.29	0.02
γ_d	-0.0447	0.0402	-1.11	0.27	-0.0510	0.0365	-1.40	0.16	-0.0653	0.0377	-1.73	0.08
γ_{lp}	0.9002	0.6089	1.48	0.14	0.0400	0.3483	0.11	0.91	0.6856	0.3750	1.83	0.07
γ_{sp}	0.0055	0.0138	0.40	0.69	-0.0003	0.0118	-0.03	0.98	-0.0105	0.0130	-0.81	0.42
γ_{sd}	-0.0053	0.0128	-0.41	0.68	0.0005	0.0127	0.04	0.97	0.0163	0.0142	1.15	0.25
γ_{rs}	0.0016	0.0093	0.17	0.87	0.0066	0.0066	1.00	0.32	0.0055	0.0086	0.64	0.52
γ_{ps}	0.0029	0.0128	0.23	0.82	0.0204	0.0103	1.99	0.05	0.0205	0.0112	1.84	0.07
δ_{dd}	-0.4514	0.2650	-1.70	0.09	-0.3009	0.2514	-1.20	0.23	-1.0574	0.2987	-3.54	0.00
δ_{dlp}	0.3716	2.9745	0.12	0.90	-1.3675	1.1486	-1.19	0.23	-0.8496	1.5320	-0.55	0.58
δ_{dsp}	0.0242	0.0649	0.37	0.71	0.0352	0.0517	0.68	0.50	0.0138	0.0620	0.22	0.82
δ_{dsd}	-0.0458	0.0504	-0.91	0.36	-0.0442	0.0479	-0.92	0.36	-0.1061	0.0617	-1.72	0.09
δ_{drs}	0.0387	0.0388	1.00	0.32	0.0414	0.0296	1.40	0.16	0.0330	0.0423	0.78	0.44
δ_{dps}	-0.0607	0.0484	-1.25	0.21	-0.0137	0.0459	-0.30	0.76	-0.1229	0.0491	-2.50	0.01
λ_{dk}	0.0206	0.0150	1.37	0.17	0.0062	0.0182	0.34	0.73	0.0118	0.0257	0.46	0.65
λ_{dl}	0.0271	0.0159	1.71	0.09	-0.0029	0.0122	-0.24	0.81	0.0229	0.0174	1.32	0.19
λ_{de}	0.0013	0.0250	0.05	0.96	-0.0025	0.0238	-0.10	0.92	0.0007	0.0300	0.02	0.98
λ_{dm}	0.0349	0.0212	1.65	0.10	-0.0062	0.0163	-0.38	0.70	0.0166	0.0262	0.63	0.53

Table A.7.1. Parameter Estimates for Rubber and Plastics (SIC 30) with Heteroskedasticity-Corrected Standard Errors, continued.

Year	1992				1997				2002			
Variable	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
λ_{lpk}	-0.0823	0.3216	-0.26	0.80	0.0253	0.1725	0.15	0.88	0.1586	0.2396	0.66	0.51
λ_{lpl}	0.0560	0.2961	0.19	0.85	-0.1051	0.1179	-0.89	0.37	0.0779	0.1616	0.48	0.63
λ_{lpe}	-0.0930	0.5194	-0.18	0.86	-0.0700	0.2172	-0.32	0.75	-0.0671	0.2794	-0.24	0.81
λ_{lpm}	0.0835	0.3825	0.22	0.83	0.1186	0.1391	0.85	0.39	0.3799	0.1939	1.96	0.05
λ_{spk}	0.0037	0.0076	0.49	0.62	0.0035	0.0068	0.51	0.61	0.0011	0.0096	0.12	0.91
λ_{spl}	-0.0001	0.0067	-0.02	0.98	0.0004	0.0046	0.08	0.94	-0.0016	0.0067	-0.23	0.81
λ_{spe}	0.0010	0.0115	0.08	0.93	-0.0002	0.0089	-0.02	0.99	0.0004	0.0124	0.03	0.97
λ_{spm}	0.0143	0.0075	1.90	0.06	0.0003	0.0057	0.06	0.96	0.0033	0.0098	0.34	0.73
λ_{sdk}	-0.0022	0.0058	-0.38	0.70	-0.0036	0.0069	-0.51	0.61	0.0008	0.0094	0.09	0.93
λ_{sdl}	0.0068	0.0055	1.24	0.22	0.0011	0.0049	0.22	0.83	0.0053	0.0070	0.75	0.45
λ_{sde}	0.0010	0.0096	0.10	0.92	0.0002	0.0091	0.03	0.98	-0.0004	0.0120	-0.04	0.97
λ_{sdm}	-0.0068	0.0069	-0.98	0.33	-0.0031	0.0057	-0.54	0.59	0.0030	0.0098	0.31	0.76
λ_{rsk}	-0.0006	0.0048	-0.12	0.90	0.0016	0.0034	0.48	0.63	0.0024	0.0051	0.47	0.64
λ_{rsl}	0.0028	0.0043	0.66	0.51	0.0033	0.0030	1.11	0.27	0.0032	0.0037	0.86	0.39
λ_{rse}	0.0012	0.0084	0.14	0.89	0.0017	0.0051	0.32	0.75	0.0016	0.0066	0.24	0.81
λ_{rsm}	-0.0073	0.0049	-1.49	0.14	0.0017	0.0033	0.52	0.60	-0.0013	0.0048	-0.27	0.79
λ_{psk}	0.0016	0.0054	0.29	0.77	-0.0028	0.0066	-0.43	0.67	0.0000	0.0055	0.00	1.00
λ_{psl}	0.0073	0.0049	1.48	0.14	0.0076	0.0042	1.81	0.07	0.0109	0.0049	2.22	0.03
λ_{pse}	-0.0003	0.0083	-0.03	0.97	-0.0003	0.0078	-0.04	0.97	0.0007	0.0080	0.09	0.93
λ_{psm}	-0.0072	0.0063	-1.14	0.25	-0.0090	0.0048	-1.88	0.06	-0.0041	0.0059	-0.70	0.49
v_{de}	0.1412	0.0150	9.40	0.00	0.1488	0.0141	10.58	0.00	0.1917	0.0168	11.39	0.00
v_{se}	-0.1908	0.0113	-16.82	0.00	-0.1742	0.0116	-15.00	0.00	-0.1591	0.0134	-11.88	0.00
v_{cr1}	-0.0191	0.0161	-1.19	0.23	0.0181	0.0134	1.34	0.18	0.0011	0.0162	0.07	0.95
v_{cr2}	-0.0044	0.0138	-0.32	0.75	0.0030	0.0147	0.21	0.84	-0.0134	0.0170	-0.79	0.43
v_{cr3}	-0.0227	0.0191	-1.19	0.23	-0.0019	0.0163	-0.12	0.91	-0.0183	0.0213	-0.86	0.39
v_{pop}	0.0238	0.0089	2.67	0.01	0.0060	0.0079	0.75	0.45	0.0008	0.0094	0.09	0.93
v_{ue}	-0.4854	0.3200	-1.52	0.13	0.6835	0.3251	2.10	0.04	-0.2514	0.5332	-0.47	0.64
v_{inc}	0.1387	0.0559	2.48	0.01	0.0949	0.0459	2.07	0.04	0.0898	0.0508	1.77	0.08
v_{dv}	1.6090	1.2634	1.27	0.20	-1.4940	1.0273	-1.45	0.15	0.5539	0.9075	0.61	0.54
ρ_{dh}	-0.0119	0.0293	-0.41	0.69	-0.0020	0.0284	-0.07	0.94	-0.0595	0.0377	-1.58	0.11
ρ_{dvh}	-0.1477	0.9970	-0.15	0.88	-0.3487	0.6419	-0.54	0.59	0.7349	0.7450	0.99	0.32
Generalized R^2			0.9992				0.9995				0.9990	
Equation Adjusted R^2												
Production Function			0.9569				0.9630				0.9485	
Capital Cost Share			0.7785				0.7963				0.7807	
Labor Cost Share			0.7506				0.7646				0.6964	
Materials Cost Share			0.8753				0.8842				0.8577	

Table A.7.2. Parameter Estimates for Metalworking Machinery (SIC 354) with Heteroskedasticity-Corrected Standard Errors.

Year	1992				1997				2002			
Variable	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
α_0	7.1519	0.0157	455.23	0.00	7.3822	0.0171	431.14	0.00	7.5604	0.0170	445.24	0.00
α_k	0.0855	0.0021	40.00	0.00	0.1239	0.0023	53.14	0.00	0.1354	0.0026	51.96	0.00
α_l	0.5615	0.0046	121.42	0.00	0.5197	0.0040	130.49	0.00	0.5048	0.0050	101.72	0.00
α_e	0.0161	0.0040	4.00	0.00	0.0138	0.0041	3.34	0.00	0.0128	0.0043	2.96	0.00
α_m	0.3080	0.0029	107.93	0.00	0.3004	0.0028	107.67	0.00	0.2936	0.0036	82.05	0.00
β_{kk}	0.0635	0.0035	18.01	0.00	0.0805	0.0066	12.16	0.00	0.0803	0.0050	16.15	0.00
β_{ll}	0.1827	0.0064	28.66	0.00	0.1749	0.0067	26.03	0.00	0.1413	0.0056	25.21	0.00
β_{ee}	0.0131	0.0081	1.63	0.10	0.0131	0.0084	1.56	0.12	0.0112	0.0053	2.13	0.03
β_{mm}	0.1701	0.0046	37.22	0.00	0.1739	0.0087	19.98	0.00	0.1540	0.0049	31.44	0.00
β_{kl}	-0.0379	0.0035	-10.79	0.00	-0.0458	0.0053	-8.71	0.00	-0.0474	0.0039	-12.20	0.00
β_{ke}	-0.0009	0.0038	-0.23	0.82	-0.0013	0.0040	-0.31	0.75	-0.0012	0.0034	-0.36	0.72
β_{km}	-0.0286	0.0025	-11.67	0.00	-0.0379	0.0032	-11.77	0.00	-0.0400	0.0034	-11.86	0.00
β_{le}	-0.0059	0.0046	-1.28	0.20	-0.0060	0.0063	-0.95	0.34	-0.0048	0.0041	-1.18	0.24
β_{lm}	-0.1400	0.0037	-37.42	0.00	-0.1313	0.0058	-22.47	0.00	-0.1194	0.0044	-26.86	0.00
β_{em}	-0.0061	0.0047	-1.30	0.19	-0.0060	0.0070	-0.87	0.39	-0.0056	0.0034	-1.67	0.10
γ_d	-0.0875	0.0416	-2.10	0.04	-0.2001	0.0405	-4.94	0.00	-0.1900	0.0530	-3.59	0.00
γ_{lp}	-0.5118	0.9997	-0.51	0.61	-2.8258	0.9456	-2.99	0.00	0.0596	0.6272	0.10	0.92
γ_{sp}	0.0245	0.0183	1.34	0.18	0.0303	0.0191	1.58	0.11	-0.0404	0.0186	-2.17	0.03
γ_{sd}	-0.0116	0.0132	-0.88	0.38	-0.0458	0.0165	-2.78	0.01	0.0252	0.0171	1.48	0.14
γ_{rs}	-0.0288	0.0105	-2.74	0.01	0.0049	0.0115	0.43	0.67	-0.0194	0.0109	-1.78	0.08
γ_{ps}	0.0760	0.0189	4.02	0.00	0.0832	0.0154	5.40	0.00	0.1058	0.0189	5.59	0.00
δ_{dd}	0.2874	0.3057	0.94	0.35	0.8210	0.2771	2.96	0.00	-0.0518	0.3657	-0.14	0.89
δ_{dlp}	-1.3681	5.1171	-0.27	0.79	-2.7493	3.4558	-0.80	0.43	0.8008	2.5915	0.31	0.76
δ_{dsp}	-0.0953	0.0869	-1.10	0.27	0.0227	0.0899	0.25	0.80	-0.0993	0.0882	-1.13	0.26
δ_{dsd}	0.0513	0.0536	0.96	0.34	0.0410	0.0629	0.65	0.51	0.1315	0.0733	1.79	0.07
δ_{drs}	0.0128	0.0414	0.31	0.76	-0.0402	0.0404	-0.99	0.32	-0.0178	0.0472	-0.38	0.71
δ_{dps}	0.0349	0.0868	0.40	0.69	0.0289	0.0589	0.49	0.62	-0.1208	0.0727	-1.66	0.10
λ_{dk}	0.0040	0.0145	0.27	0.78	0.0080	0.0149	0.53	0.59	0.0193	0.0190	1.02	0.31
λ_{dl}	-0.0252	0.0194	-1.30	0.19	-0.0302	0.0180	-1.68	0.09	-0.0003	0.0245	-0.01	0.99
λ_{de}	-0.0015	0.0253	-0.06	0.95	0.0010	0.0282	0.04	0.97	0.0008	0.0295	0.03	0.98
λ_{dm}	0.0226	0.0151	1.50	0.13	0.0285	0.0190	1.50	0.13	0.0314	0.0213	1.48	0.14

Table A.7.2. Parameter Estimates for Metalworking Machinery (SIC 354) with Heteroskedasticity-Corrected Standard Errors, continued.

Year	1992				1997				2002			
Variable	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
λ_{lpk}	-0.0502	0.3853	-0.13	0.90	-0.0719	0.3777	-0.19	0.85	0.0476	0.2326	0.20	0.84
λ_{lpl}	0.4071	0.5156	0.79	0.43	0.1668	0.3873	0.43	0.67	0.5938	0.3251	1.83	0.07
λ_{lpe}	0.0553	0.6585	0.08	0.93	-0.0660	0.5836	-0.11	0.91	-0.0627	0.3875	-0.16	0.87
λ_{lpm}	-0.0204	0.4381	-0.05	0.96	0.0397	0.3035	0.13	0.90	0.1275	0.2743	0.46	0.64
λ_{spk}	0.0031	0.0064	0.48	0.63	0.0006	0.0108	0.06	0.96	-0.0008	0.0089	-0.09	0.93
λ_{spl}	0.0082	0.0093	0.87	0.38	0.0044	0.0104	0.42	0.67	-0.0149	0.0110	-1.35	0.18
λ_{spe}	-0.0010	0.0114	-0.09	0.93	0.0005	0.0159	0.03	0.98	0.0003	0.0127	0.02	0.98
λ_{spm}	0.0099	0.0074	1.33	0.18	-0.0010	0.0089	-0.11	0.91	-0.0045	0.0089	-0.50	0.62
λ_{sdk}	-0.0020	0.0040	-0.49	0.63	-0.0023	0.0083	-0.28	0.78	0.0030	0.0070	0.43	0.67
λ_{sdl}	-0.0056	0.0061	-0.93	0.35	0.0024	0.0085	0.28	0.78	0.0228	0.0089	2.56	0.01
λ_{sde}	0.0012	0.0072	0.16	0.87	0.0001	0.0123	0.01	0.99	-0.0004	0.0104	-0.04	0.97
λ_{sdm}	-0.0063	0.0048	-1.29	0.20	-0.0005	0.0064	-0.08	0.94	0.0104	0.0075	1.39	0.17
λ_{rsk}	0.0003	0.0035	0.08	0.93	0.0006	0.0048	0.12	0.91	-0.0023	0.0052	-0.44	0.66
λ_{rsl}	0.0049	0.0053	0.92	0.36	-0.0103	0.0047	-2.19	0.03	-0.0098	0.0061	-1.62	0.10
λ_{rse}	0.0014	0.0064	0.22	0.82	0.0015	0.0071	0.21	0.84	0.0011	0.0075	0.14	0.89
λ_{rsm}	0.0015	0.0036	0.42	0.68	0.0018	0.0040	0.45	0.66	-0.0042	0.0050	-0.85	0.40
λ_{psk}	-0.0011	0.0064	-0.18	0.86	0.0028	0.0063	0.44	0.66	0.0009	0.0071	0.13	0.89
λ_{psl}	0.0017	0.0098	0.17	0.86	0.0036	0.0075	0.47	0.64	0.0120	0.0090	1.34	0.18
λ_{pse}	0.0008	0.0119	0.07	0.95	0.0014	0.0105	0.14	0.89	0.0005	0.0099	0.05	0.96
λ_{psm}	-0.0037	0.0070	-0.53	0.60	0.0048	0.0063	0.76	0.45	0.0002	0.0074	0.02	0.98
v_{de}	0.1779	0.0205	8.69	0.00	0.2099	0.0193	10.86	0.00	0.2165	0.0240	9.00	0.00
v_{se}	-0.1732	0.0136	-12.77	0.00	-0.1249	0.0131	-9.51	0.00	-0.1583	0.0172	-9.18	0.00
v_{cr1}	-0.0248	0.0250	-0.99	0.32	0.0774	0.0237	3.27	0.00	-0.0139	0.0278	-0.50	0.62
v_{cr2}	0.0145	0.0173	0.83	0.40	0.0665	0.0202	3.30	0.00	0.0345	0.0194	1.77	0.08
v_{cr3}	-0.0848	0.0263	-3.23	0.00	0.0069	0.0241	0.28	0.78	-0.0969	0.0311	-3.12	0.00
v_{pop}	0.0359	0.0103	3.49	0.00	0.0156	0.0092	1.71	0.09	0.0215	0.0133	1.61	0.11
v_{ue}	0.5893	0.3663	1.61	0.11	-0.1135	0.6947	-0.16	0.87	2.1589	0.8288	2.60	0.01
v_{inc}	-0.0238	0.0789	-0.30	0.76	-0.1051	0.0760	-1.38	0.17	-0.1869	0.0971	-1.92	0.05
v_{dv}	-3.1462	1.2815	-2.46	0.01	-4.0410	1.4463	-2.79	0.01	-4.0307	1.4058	-2.87	0.00
ρ_{dh}	-0.0179	0.0410	-0.44	0.66	-0.0143	0.0368	-0.39	0.70	0.2221	0.0513	4.33	0.00
ρ_{dvh}	0.5574	1.0978	0.51	0.61	-0.9196	0.8130	-1.13	0.26	-0.4974	1.1745	-0.42	0.67
Generalized R^2			0.9989				0.9991				0.9986	
Equation Adjusted R^2												
Production Function			0.9420				0.9517				0.9351	
Capital Cost Share			0.7612				0.7576				0.7535	
Labor Cost Share			0.7445				0.7388				0.7367	
Materials Cost Share			0.8512				0.8784				0.8576	

Table A.7.3. Parameter Estimates for Measuring and Controlling Devices (SIC 382) with Heteroskedasticity-Corrected Standard Errors.

Year	1992				1997				2002			
Variable	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
α_0	8.2787	0.0417	198.59	0.00	8.4910	0.0289	294.04	0.00	8.7729	0.0484	181.34	0.00
α_k	0.0935	0.0059	15.72	0.00	0.1222	0.0054	22.69	0.00	0.1280	0.0058	22.09	0.00
α_l	0.4313	0.0082	52.82	0.00	0.3983	0.0083	48.16	0.00	0.3958	0.0089	44.36	0.00
α_e	0.0105	0.0127	0.83	0.41	0.0093	0.0084	1.10	0.27	0.0075	0.0107	0.70	0.48
α_m	0.3737	0.0141	26.51	0.00	0.3772	0.0078	48.62	0.00	0.3670	0.0086	42.53	0.00
β_{kk}	0.0720	0.0351	2.05	0.04	0.0731	0.0081	9.06	0.00	0.0649	0.0210	3.09	0.00
β_{ll}	0.1354	0.0213	6.35	0.00	0.1208	0.0084	14.31	0.00	0.1208	0.0134	9.01	0.00
β_{ee}	0.0083	0.0442	0.19	0.85	0.0091	0.0108	0.85	0.40	0.0064	0.0236	0.27	0.79
β_{mm}	0.1458	0.0213	6.83	0.00	0.1583	0.0123	12.89	0.00	0.1451	0.0132	10.99	0.00
β_{kl}	-0.0356	0.0306	-1.16	0.24	-0.0258	0.0042	-6.19	0.00	-0.0264	0.0152	-1.73	0.08
β_{ke}	-0.0002	0.0414	-0.01	1.00	-0.0020	0.0080	-0.25	0.80	-0.0008	0.0135	-0.06	0.95
β_{km}	-0.0397	0.0284	-1.40	0.16	-0.0485	0.0080	-6.05	0.00	-0.0431	0.0171	-2.52	0.01
β_{le}	-0.0031	0.0276	-0.11	0.91	-0.0016	0.0068	-0.23	0.82	-0.0019	0.0102	-0.18	0.85
β_{lm}	-0.1080	0.0248	-4.36	0.00	-0.1075	0.0058	-18.54	0.00	-0.1049	0.0136	-7.69	0.00
β_{em}	-0.0051	0.0312	-0.16	0.87	-0.0053	0.0057	-0.94	0.35	-0.0037	0.0086	-0.44	0.66
γ_d	-0.3532	0.1761	-2.01	0.05	-0.2499	0.1440	-1.74	0.08	0.1184	0.1734	0.68	0.49
γ_{lp}	1.3261	0.8182	1.62	0.11	0.3648	0.6008	0.61	0.54	-0.2681	0.9055	-0.30	0.77
γ_{sp}	-0.0222	0.0261	-0.85	0.39	0.0285	0.0179	1.59	0.11	-0.0036	0.0201	-0.18	0.86
γ_{sd}	0.0029	0.0209	0.14	0.89	-0.0173	0.0168	-1.03	0.30	-0.0166	0.0222	-0.75	0.45
γ_{rs}	0.0238	0.0103	2.32	0.02	0.0174	0.0092	1.89	0.06	0.0111	0.0132	0.84	0.40
γ_{ps}	0.0907	0.0418	2.17	0.03	0.0820	0.0380	2.16	0.03	0.0607	0.0466	1.30	0.19
δ_{dd}	1.2189	0.9634	1.27	0.21	2.7059	1.3996	1.93	0.05	-3.0457	1.6421	-1.85	0.06
δ_{dlp}	7.8619	4.7448	1.66	0.10	-3.2199	3.4837	-0.92	0.36	-6.7057	6.2829	-1.07	0.29
δ_{dsp}	-0.1091	0.1722	-0.63	0.53	0.1146	0.1092	1.05	0.29	-0.3717	0.1813	-2.05	0.04
δ_{dsd}	0.0706	0.1129	0.63	0.53	-0.1726	0.1011	-1.71	0.09	0.1565	0.1366	1.15	0.25
δ_{drs}	-0.0127	0.0530	-0.24	0.81	0.0575	0.0579	0.99	0.32	-0.1388	0.0719	-1.93	0.05
δ_{dps}	0.0251	0.2832	0.09	0.93	0.1176	0.2678	0.44	0.66	0.6262	0.3207	1.95	0.05
λ_{dk}	0.0074	0.0751	0.10	0.92	-0.0029	0.0442	-0.06	0.95	-0.0053	0.0471	-0.11	0.91
λ_{dl}	0.0640	0.0625	1.02	0.31	0.0349	0.0364	0.96	0.34	0.0236	0.0556	0.42	0.67
λ_{de}	-0.0039	0.1173	-0.03	0.97	-0.0055	0.0675	-0.08	0.94	-0.0021	0.0781	-0.03	0.98
λ_{dm}	0.0360	0.0421	0.86	0.39	0.0235	0.0384	0.61	0.54	-0.0037	0.0458	-0.08	0.94

Table A.7.3. Parameter Estimates for Measuring and Controlling Devices (SIC 382) with Heteroskedasticity-Corrected Standard Errors, continued.

Year	1992				1997				2002			
Variable	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
λ_{lpk}	-0.5054	0.5992	-0.84	0.40	-0.0970	0.2257	-0.43	0.67	0.1686	0.7130	0.24	0.81
λ_{lpl}	-1.3694	0.5377	-2.55	0.01	0.0100	0.2734	0.04	0.97	0.3340	0.4975	0.67	0.50
λ_{lpe}	-0.0015	0.9373	0.00	1.00	-0.0112	0.4146	-0.03	0.98	-0.0253	0.7521	-0.03	0.97
λ_{lpm}	-1.3705	0.4876	-2.81	0.01	-0.4166	0.2441	-1.71	0.09	-0.0436	0.4786	-0.09	0.93
λ_{spk}	0.0096	0.0121	0.80	0.43	0.0030	0.0073	0.41	0.68	0.0032	0.0084	0.37	0.71
λ_{spl}	0.0283	0.0136	2.09	0.04	0.0045	0.0078	0.58	0.56	0.0040	0.0091	0.44	0.66
λ_{spe}	0.0013	0.0208	0.06	0.95	0.0002	0.0122	0.01	0.99	0.0011	0.0148	0.07	0.94
λ_{spm}	0.0295	0.0132	2.24	0.03	0.0057	0.0102	0.56	0.58	0.0101	0.0097	1.04	0.30
λ_{sdk}	-0.0053	0.0099	-0.54	0.59	-0.0028	0.0067	-0.42	0.68	-0.0043	0.0123	-0.35	0.73
λ_{sdl}	-0.0160	0.0088	-1.80	0.07	-0.0006	0.0066	-0.09	0.93	-0.0013	0.0115	-0.11	0.91
λ_{sde}	-0.0006	0.0138	-0.05	0.96	0.0001	0.0103	0.01	0.99	-0.0009	0.0180	-0.05	0.96
λ_{sdm}	-0.0190	0.0081	-2.35	0.02	-0.0046	0.0098	-0.47	0.64	-0.0139	0.0102	-1.36	0.17
λ_{rsk}	-0.0006	0.0049	-0.13	0.90	-0.0015	0.0039	-0.38	0.70	0.0009	0.0107	0.09	0.93
λ_{rsl}	0.0129	0.0059	2.19	0.03	0.0086	0.0041	2.08	0.04	0.0048	0.0078	0.61	0.54
λ_{rse}	-0.0002	0.0084	-0.02	0.98	-0.0002	0.0060	-0.03	0.97	0.0004	0.0165	0.03	0.98
λ_{rsm}	0.0032	0.0060	0.53	0.60	-0.0022	0.0041	-0.53	0.59	0.0010	0.0072	0.14	0.89
λ_{psk}	0.0002	0.0349	0.00	1.00	-0.0009	0.0153	-0.06	0.95	0.0042	0.0347	0.12	0.90
λ_{psl}	0.0271	0.0245	1.11	0.27	0.0169	0.0137	1.23	0.22	0.0281	0.0271	1.04	0.30
λ_{pse}	-0.0009	0.0444	-0.02	0.98	0.0013	0.0221	0.06	0.95	0.0005	0.0604	0.01	0.99
λ_{psm}	-0.0033	0.0234	-0.14	0.89	0.0023	0.0172	0.13	0.90	-0.0022	0.0250	-0.09	0.93
v_{de}	0.2313	0.0457	5.06	0.00	0.2507	0.0470	5.34	0.00	0.2750	0.0402	6.85	0.00
v_{se}	-0.2715	0.0517	-5.26	0.00	-0.2542	0.0431	-5.90	0.00	-0.2216	0.0344	-6.45	0.00
v_{cr1}	0.0188	0.0380	0.50	0.62	-0.0078	0.0375	-0.21	0.83	-0.0892	0.0524	-1.70	0.09
v_{cr2}	-0.0066	0.0378	-0.17	0.86	-0.0243	0.0415	-0.59	0.56	-0.1172	0.0454	-2.58	0.01
v_{cr3}	0.0150	0.0317	0.47	0.64	0.0769	0.0359	2.14	0.03	-0.0804	0.0547	-1.47	0.14
v_{pop}	-0.0132	0.0316	-0.42	0.68	0.0486	0.0227	2.14	0.03	0.0765	0.0272	2.81	0.01
v_{ue}	-0.8074	1.1795	-0.68	0.49	-2.8199	1.3128	-2.15	0.03	1.5269	2.1250	0.72	0.47
v_{inc}	-0.3069	0.1418	-2.16	0.03	-0.0912	0.1360	-0.67	0.50	-0.0915	0.1666	-0.55	0.58
v_{dv}	-22.1439	8.5591	-2.59	0.01	-9.5446	5.8248	-1.64	0.10	-5.8544	9.6580	-0.61	0.54
ρ_{dh}	-0.0642	0.1126	-0.57	0.57	0.1107	0.0763	1.45	0.15	0.0283	0.0994	0.28	0.78
ρ_{dvh}	1.1099	7.8768	0.14	0.89	3.9798	4.0100	0.99	0.32	-4.1376	7.3760	-0.56	0.57
Generalized R^2			0.9983				0.9984				0.9975	
Equation Adjusted R^2												
Production Function			0.9409				0.9455				0.9372	
Capital Cost Share			0.7461				0.7629				0.6756	
Labor Cost Share			0.6553				0.6463				0.6209	
Materials Cost Share			0.8026				0.8371				0.7896	

Appendix 8. Marginal Impacts of Alternative Regional Industrial Dominance Indicators Across Ranges of Standard Inputs and Agglomeration Economies

Figures A.8.1, A.8.2, and A.8.3 are the equivalents of Figure 7.2 in the text for the Herfindahl-Hirschman, Rosenbluth, and Gini measures of regional industrial dominance, respectively. Figures A.8.4, A.8.5, and A.8.6 are equivalent to Figure 7.3.

Figure A.8.1. Marginal Impacts of Herfindahl-Hirschman Regional Industrial Dominance Across Range of Standard Inputs.

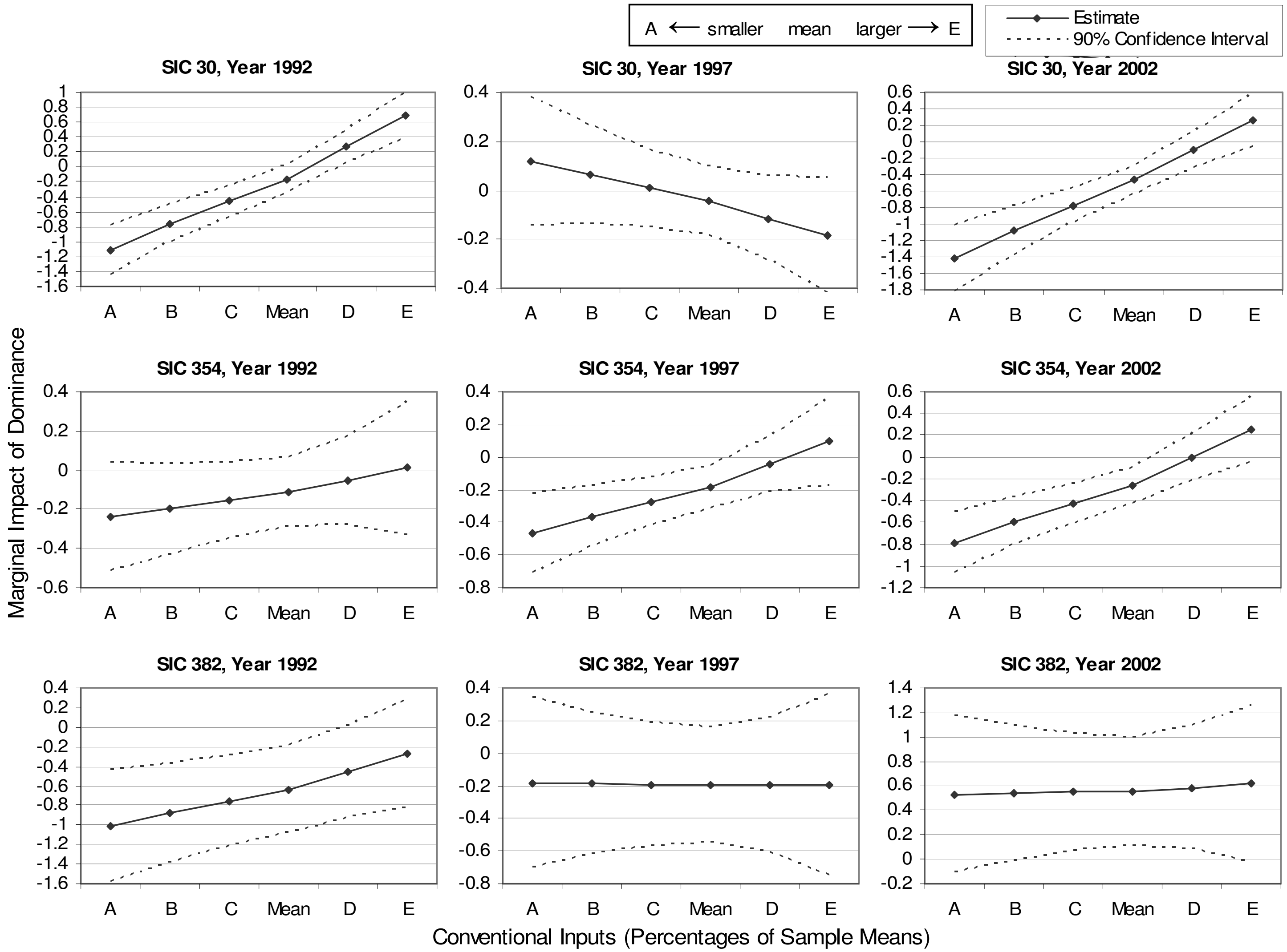


Figure A.8.2. Marginal Impacts of Rosenbluth Regional Industrial Dominance Across Range of Standard Inputs.

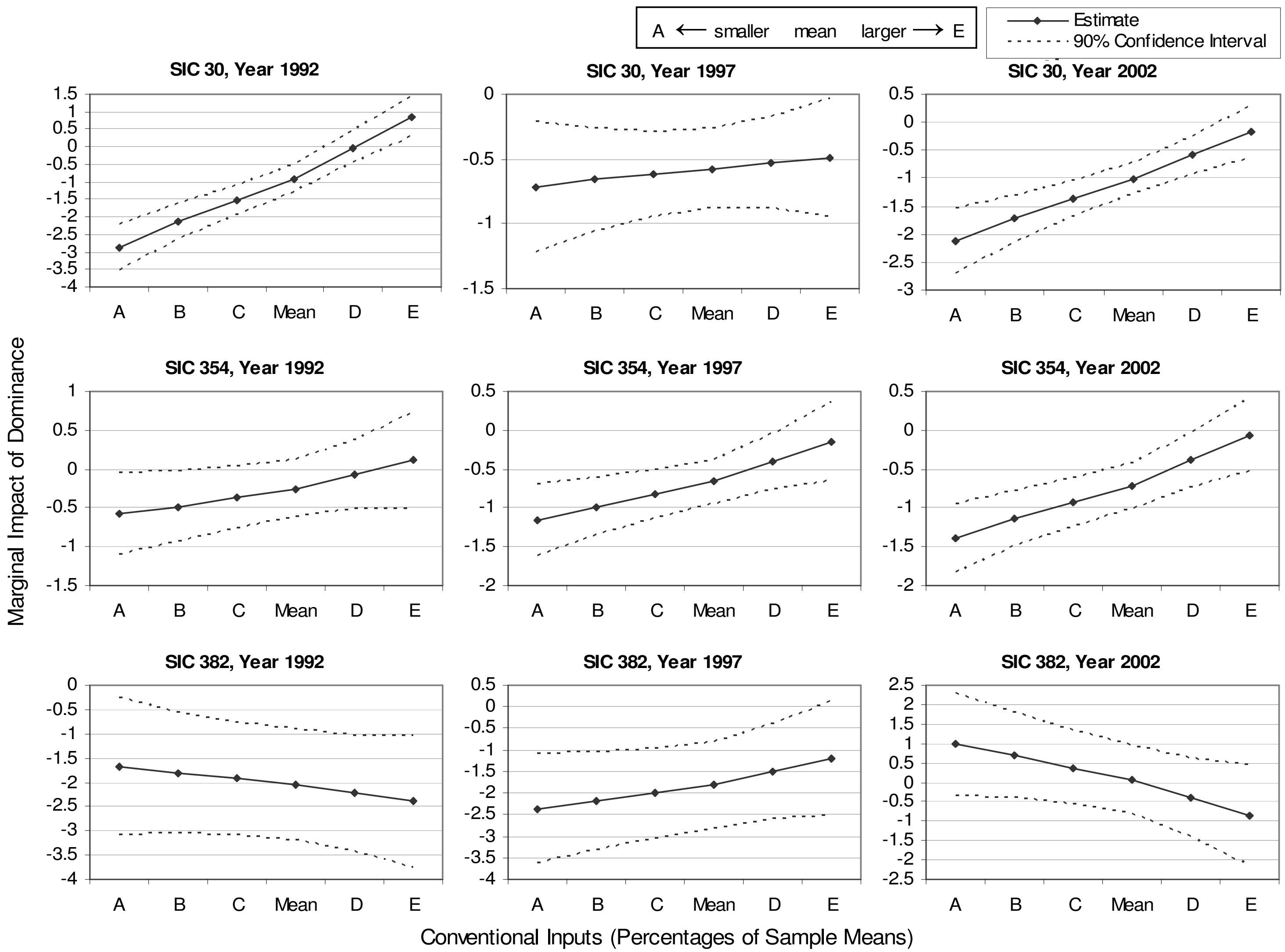


Figure A.8.3. Marginal Impacts of Gini Regional Industrial Dominance Across Range of Standard Inputs.

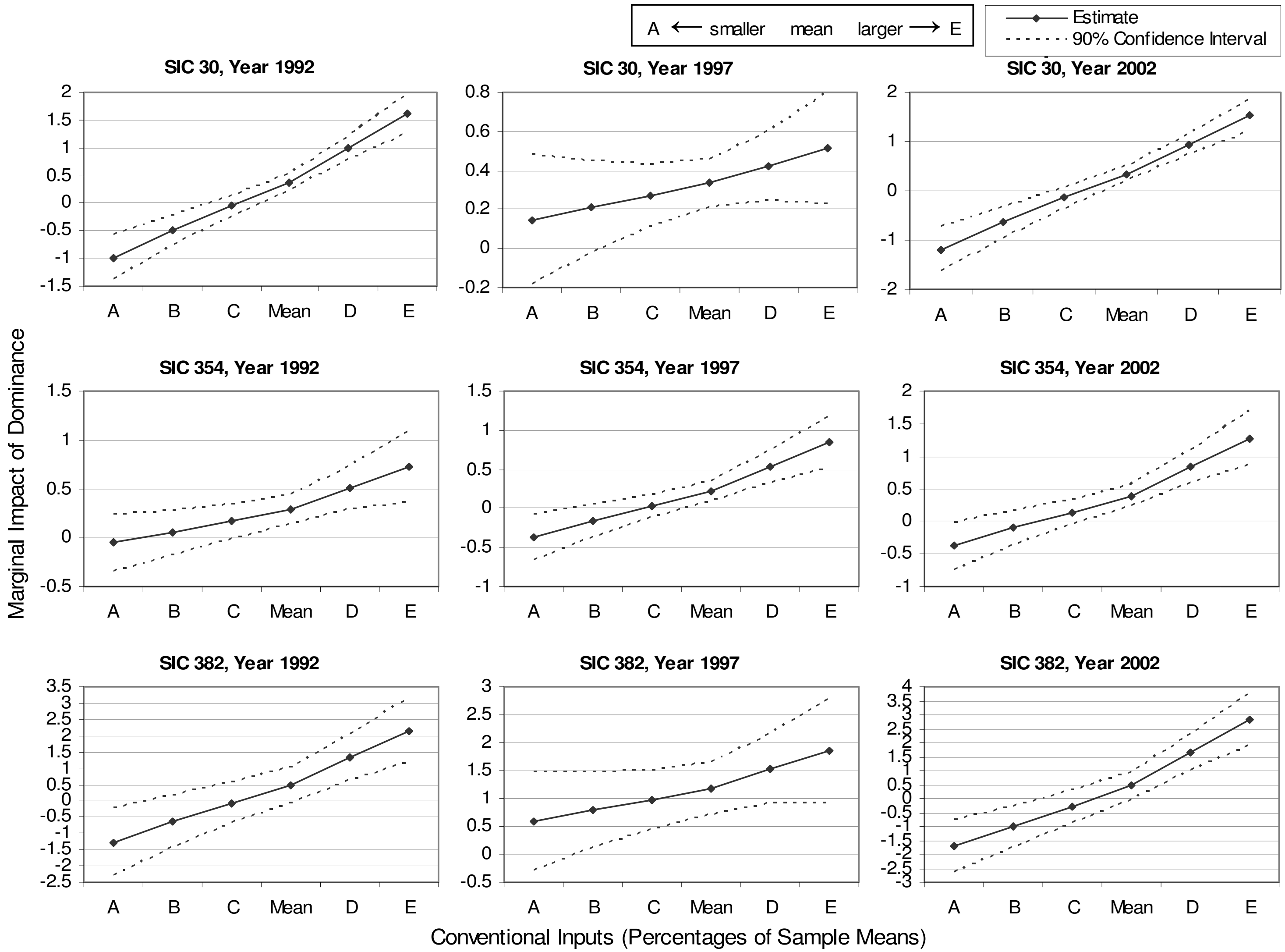


Figure A.8.4. Marginal Impacts of Herfindahl-Hirschman Regional Industrial Dominance Across Agglomeration Economies Range.

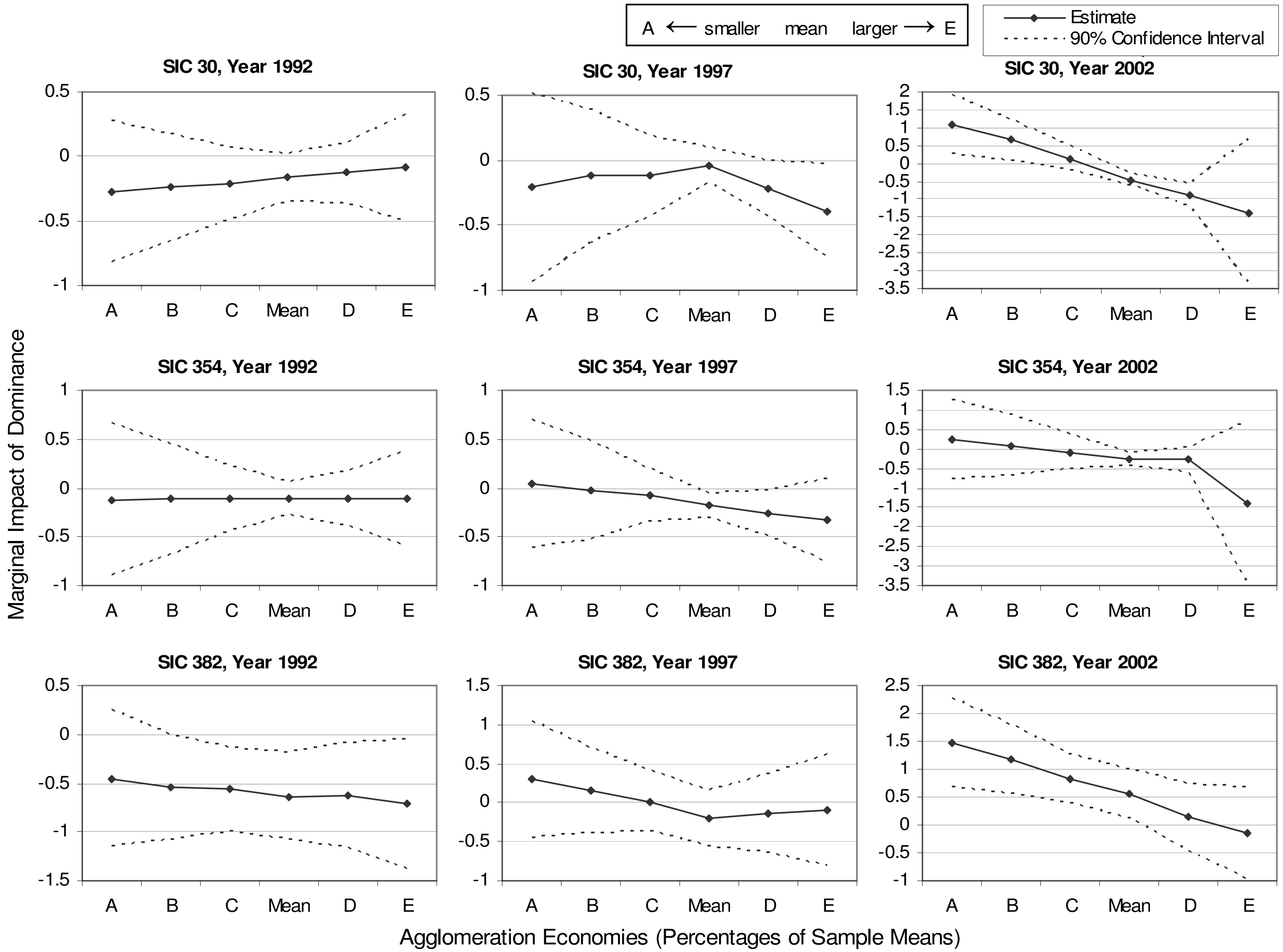


Figure A.8.5. Marginal Impacts of Rosenbluth Regional Industrial Dominance Across Agglomeration Economies Range.

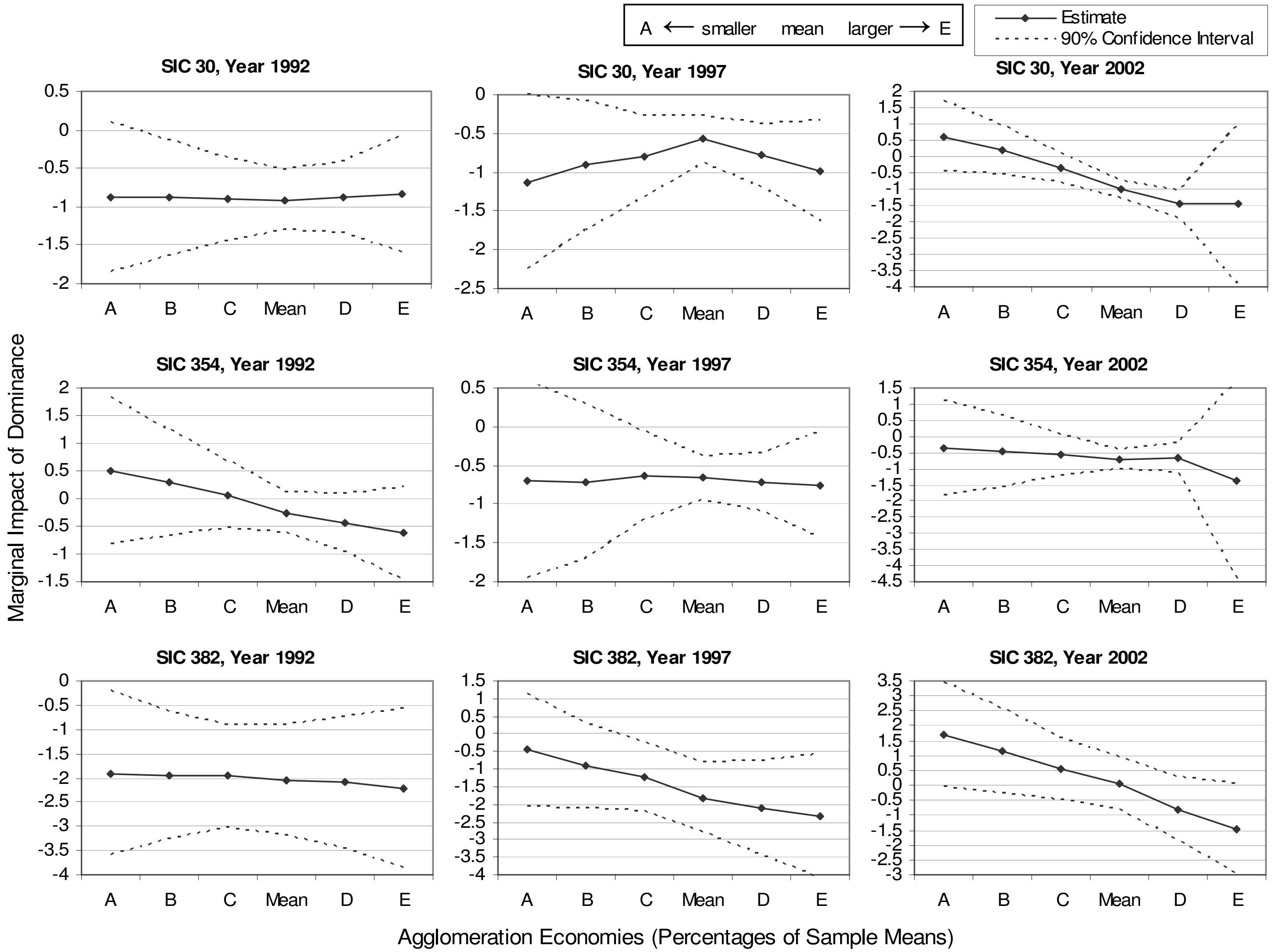
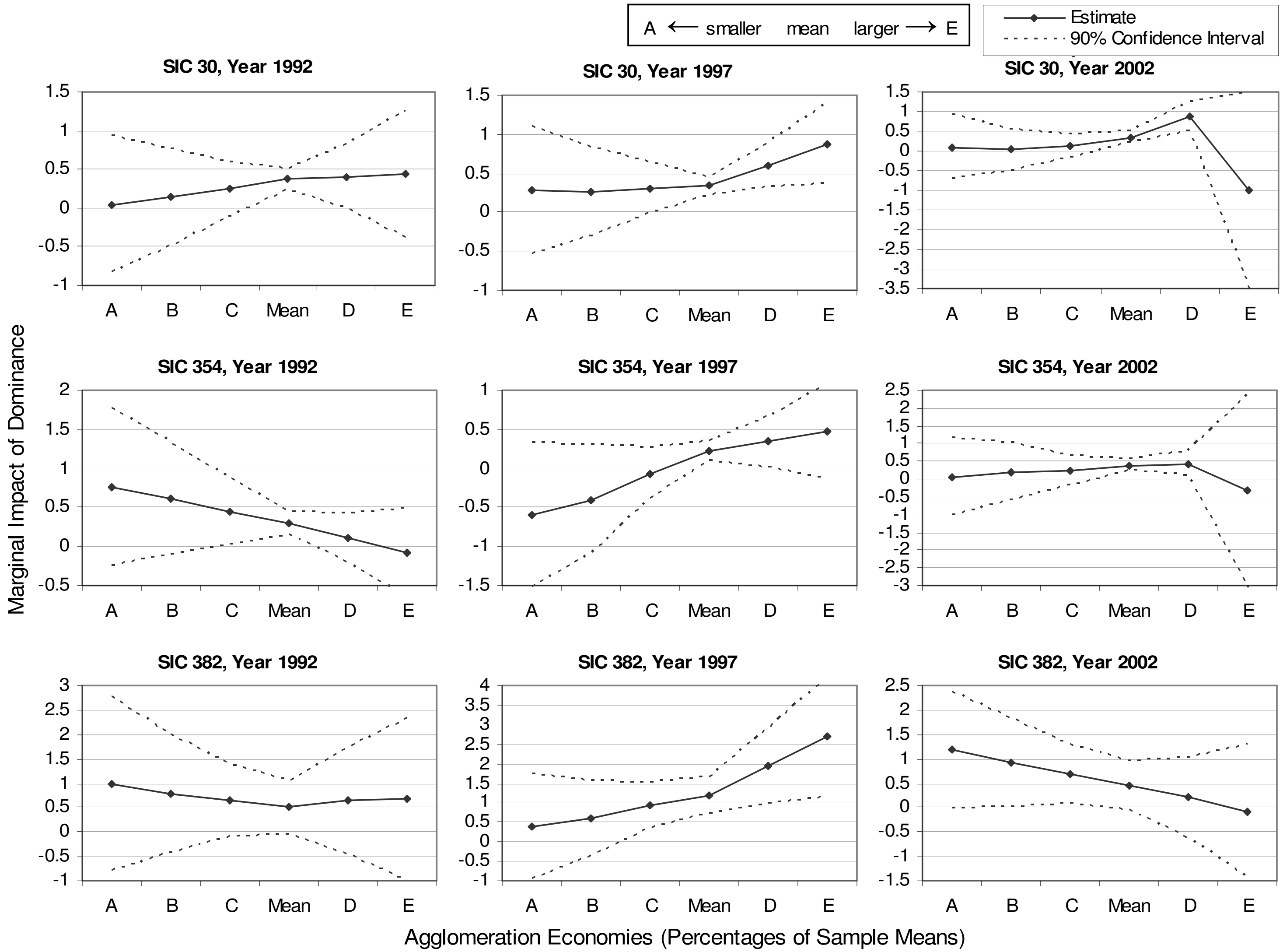


Figure A.8.6. Marginal Impacts of Gini Regional Industrial Dominance Across Agglomeration Economies Range.



Appendix 9. Alternative Agglomeration Economy Spatial Decay Profiles

Tables A.9.1, A.9.2, and A.9.3 display the information equivalent to that in Table 6.3 in the text for the labor pooling, manufactured input supply pooling, producer services pooling, and academic research expenditures measures calculated with the alternative spatial decay profiles described in Chapter Eight. All distances are in miles.

Table A.9.1. Alternative Agglomeration Economy Variables for Rubber and Plastics (SIC 30): Descriptive Information.

Year / Sample observations	1992 (n = 6,747)			1997 (n = 8,000)			2002 (n = 6,546)		
	mean	std dev	%>mean	mean	std dev	%>mean	mean	std dev	%>mean
Labor Pooling									
α = 0.1, distance = 50	0.0784	0.0147	35.27	0.0979	0.0277	41.56	0.1180	0.0311	44.23
α = 0.1, distance = 75 (default)	0.0781	0.0129	39.32	0.0974	0.0249	42.76	0.1171	0.0279	44.70
α = 0.1, distance = 100	0.0773	0.0113	44.89	0.0962	0.0224	44.98	0.1156	0.0251	46.96
α = 0.5, distance = 75	0.0778	0.0134	40.91	0.0968	0.0255	41.16	0.1165	0.0286	43.95
α = 1.0, distance = 75	0.0794	0.0161	42.06	0.0989	0.0295	40.28	0.1193	0.0333	42.21
Manufactured Inputs									
α = 0.1, distance = 50	1,904	1,565	34.15	1,157	996	38.18	1,036	909	37.37
α = 0.1, distance = 75 (default)	2,913	2,071	42.00	1,807	1,356	40.68	1,635	1,212	40.90
α = 0.1, distance = 100	4,141	2,683	49.36	2,585	1,759	42.76	2,356	1,554	44.01
α = 0.5, distance = 75	1,031	897	34.50	633	534	37.66	565	503	39.47
α = 1.0, distance = 75	561	751	34.79	342	437	33.46	301	415	30.87
Producer Services									
α = 0.1, distance = 50	17,821	22,137	29.98	8,567	10,138	32.24	9,256	11,184	32.86
α = 0.1, distance = 75 (default)	25,567	28,550	27.95	12,517	13,345	30.88	13,878	15,073	30.58
α = 0.1, distance = 100	34,738	35,059	29.67	17,312	16,754	27.26	19,315	18,776	26.93
α = 0.5, distance = 75	9,005	8,499	35.27	4,511	4,141	36.19	4,903	4,747	34.56
α = 1.0, distance = 75	4,701	4,979	37.22	2,461	2,735	34.63	2,627	3,203	32.83
Research									
α = 0.1, distance = 50	71,605	83,042	34.27	80,817	90,614	39.63	91,193	104,659	39.38
α = 0.1, distance = 200 (default)	330,729	242,436	38.94	406,037	274,997	41.69	501,543	322,954	41.87
α = 0.1, distance = 300	531,526	320,542	50.44	657,110	378,881	51.38	823,065	449,876	51.36
α = 0.5, distance = 200	68,816	53,056	37.28	83,401	59,327	41.20	99,783	68,342	43.26
α = 1.0, distance = 200	22,600	34,996	28.04	27,315	41,560	26.05	30,717	48,011	24.43

Table A.9.2. Alternative Agglomeration Economy Variables for Metalworking Machinery (SIC 354): Descriptive Information.

Year / Sample observations	1992 (n = 5,189)			1997 (n = 5,490)			2002 (n = 4,161)		
	mean	std dev	%>mean	mean	std dev	%>mean	mean	std dev	%>mean
Labor Pooling									
α = 0.1, distance = 50	0.1187	0.0118	46.73	0.1473	0.0157	55.43	0.1246	0.0229	55.30
α = 0.1, distance = 75 (default)	0.1170	0.0109	47.95	0.1457	0.0145	55.01	0.1221	0.0204	56.28
α = 0.1, distance = 100	0.1156	0.0103	44.96	0.1446	0.0140	51.91	0.1202	0.0190	56.79
α = 0.5, distance = 75	0.1187	0.0126	46.41	0.1465	0.0152	54.68	0.1228	0.0211	53.40
α = 1.0, distance = 75	0.1212	0.0158	41.53	0.1491	0.0179	49.95	0.1263	0.0246	51.77
Manufactured Inputs									
α = 0.1, distance = 50	2,233	1,513	38.81	2,026	1,330	42.28	1,845	1,261	41.41
α = 0.1, distance = 75 (default)	3,297	1,883	48.20	3,025	1,650	47.74	2,797	1,609	45.61
α = 0.1, distance = 100	4,650	2,399	54.83	4,311	2,143	55.23	4,030	2,112	52.30
α = 0.5, distance = 75	1,238	805	40.10	1,119	714	40.86	1,014	658	41.65
α = 1.0, distance = 75	722	637	35.36	644	577	38.09	571	517	39.17
Producer Services									
α = 0.1, distance = 50	14,840	17,005	36.89	6,591	7,279	38.00	6,954	8,031	38.02
α = 0.1, distance = 75 (default)	22,113	22,927	31.18	9,866	9,857	30.46	10,660	11,130	30.09
α = 0.1, distance = 100	31,771	29,590	26.31	14,119	12,604	24.75	15,587	14,594	24.35
α = 0.5, distance = 75	7,992	6,878	34.69	3,573	3,078	35.37	3,801	3,556	34.17
α = 1.0, distance = 75	4,386	4,199	36.37	1,973	2,044	34.77	2,068	2,358	33.12
Research									
α = 0.1, distance = 50	90,523	119,538	38.27	126,233	157,162	35.81	142,452	178,397	35.38
α = 0.1, distance = 200 (default)	497,467	377,447	38.95	725,256	475,313	39.69	924,617	555,602	44.20
α = 0.1, distance = 300	951,010	530,637	34.92	1,355,860	697,026	42.39	1,736,869	814,152	49.15
α = 0.5, distance = 200	97,856	82,525	34.26	140,113	101,366	35.92	173,752	118,158	41.43
α = 1.0, distance = 200	28,966	58,476	22.26	39,650	74,452	21.64	47,170	87,304	20.33

Table A.9.3. Alternative Agglomeration Economy Variables for Measuring/Controlling Devices (SIC 382): Descriptive Information.

Year / Sample observations	1992 (n = 1,384)			1997 (n = 1,540)			2002 (n = 1,201)		
	mean	std dev	%>mean	mean	std dev	%>mean	mean	std dev	%>mean
Labor Pooling									
α = 0.1, distance = 50	0.1307	0.0112	47.90	0.1887	0.0161	47.27	0.1464	0.0169	50.46
α = 0.1, distance = 75	0.1275	0.0077	47.69	0.1845	0.0119	49.09	0.1438	0.0139	61.95
α = 0.1, distance = 100	0.1258	0.0066	50.58	0.1822	0.0104	52.14	0.1422	0.0126	61.62
α = 0.5, distance = 75	0.1322	0.0133	38.01	0.1904	0.0190	43.12	0.1476	0.0198	43.38
α = 1.0, distance = 75 (default)	0.1369	0.0201	39.45	0.1958	0.0265	42.53	0.1514	0.0259	40.88
Manufactured Inputs									
α = 0.1, distance = 50	4,029	2,863	40.82	4,683	4,771	30.13	4,396	3,922	34.39
α = 0.1, distance = 75	5,271	3,275	47.76	5,775	4,800	40.00	5,468	3,991	43.96
α = 0.1, distance = 100	6,658	3,724	50.36	6,971	4,806	44.81	6,647	4,143	47.96
α = 0.5, distance = 75	2,445	2,172	31.14	3,063	4,100	22.92	2,746	3,201	27.56
α = 1.0, distance = 75 (default)	1,728	2,167	25.22	2,374	4,113	18.31	2,051	3,194	22.90
Producer Services									
α = 0.1, distance = 50	22,171	18,588	35.91	13,041	10,158	35.32	15,391	11,760	42.71
α = 0.1, distance = 75	29,855	24,932	33.38	17,418	13,974	31.95	20,658	16,416	37.72
α = 0.1, distance = 100	38,327	31,018	23.84	22,230	17,705	21.49	26,050	20,572	30.89
α = 0.5, distance = 75	11,816	6,746	44.22	7,084	4,055	48.64	8,428	5,014	46.54
α = 1.0, distance = 75 (default)	7,089	4,425	50.51	4,401	3,039	47.79	5,268	3,809	46.54
Research									
α = 0.1, distance = 50	351,894	324,155	36.49	404,162	359,165	39.42	455,715	369,934	42.80
α = 0.1, distance = 200	976,528	693,341	42.56	1,168,589	827,246	39.61	1,349,064	878,821	44.13
α = 0.1, distance = 300	1,508,751	971,866	46.17	1,849,187	1,211,985	45.78	2,166,647	1,325,504	49.71
α = 0.5, distance = 200	287,981	237,962	42.41	338,027	277,223	40.58	379,065	270,459	40.13
α = 1.0, distance = 200 (default)	160,186	229,831	22.90	185,002	267,781	29.48	201,325	261,265	27.81

Appendix 10. Economy-Wide Dominance

Table A.10.1 displays the mean, standard deviation, and percent of observations above the mean for the measures of regional manufacturing dominance and regional economy-wide dominance. Tables A.10.2, A.10.3, and A.10.4 contain the coefficient estimates, standard errors, t-statistics, and probability values obtained from re-evaluating the four-equation system with a manufacturing or overall regional dominance control added to the production function, along with a repeat of the base model results that do not include an economy-wide dominance variable.

Table A.10.1. Economy-Wide Dominance Variables: Descriptive Information.

SIC 30: Rubber and Plastics.										
Year		1992 (n = 6,747)			1997 (n = 8,000)			2002 (n = 6,546)		
		mean	std dev	%>mean	mean	std dev	%>mean	mean	std dev	%>mean
Manufacturing Dominance										
Concentratio Ratio	DM_C	0.4410	0.1410	44.79	0.4529	0.1448	46.79	0.4804	0.1442	46.93
Herfindahl-Hirschman	DM_H	0.0447	0.0586	30.74	0.0456	0.0535	32.41	0.0523	0.0593	33.41
Rosenbluth	DM_R	0.0053	0.0054	31.42	0.0062	0.0072	32.91	0.0076	0.0083	30.72
Gini	DM_G	0.8860	0.0299	47.95	0.8942	0.0286	49.28	0.8930	0.0279	43.54
Economy-Wide Dominance										
Concentratio Ratio	DO_C	0.1440	0.0453	41.81	0.1385	0.0438	45.13	0.1450	0.0518	41.57
Herfindahl-Hirschman	DO_H	0.0030	0.0021	33.42	0.0026	0.0018	37.84	0.0030	0.0029	30.78
Rosenbluth	DO_R	0.0003	0.0002	34.42	0.0003	0.0003	34.81	0.0003	0.0003	35.01
Gini	DO_G	0.8485	0.0152	53.43	0.8478	0.0152	57.54	0.8266	0.0218	56.02

SIC 354: Metalworking Machinery.										
Year		1992 (n = 5,189)			1997 (n = 5,490)			2002 (n = 4,161)		
		mean	std dev	%>mean	mean	std dev	%>mean	mean	std dev	%>mean
Manufacturing Dominance										
Concentratio Ratio	DM_C	0.4779	0.1576	48.85	0.4699	0.1541	48.49	0.4886	0.1542	47.20
Herfindahl-Hirschman	DM_H	0.0589	0.0651	36.81	0.0554	0.0608	33.59	0.0549	0.0562	37.61
Rosenbluth	DM_R	0.0055	0.0073	30.47	0.0055	0.0070	32.15	0.0065	0.0085	28.86
Gini	DM_G	0.8902	0.0319	49.22	0.8959	0.0306	45.25	0.8956	0.0312	45.33
Economy-Wide Dominance										
Concentratio Ratio	DO_C	0.1558	0.0482	44.36	0.1394	0.0403	50.22	0.1399	0.0420	48.11
Herfindahl-Hirschman	DO_H	0.0038	0.0031	36.71	0.0027	0.0020	40.64	0.0026	0.0022	35.30
Rosenbluth	DO_R	0.0003	0.0003	32.70	0.0003	0.0003	32.40	0.0003	0.0003	33.81
Gini	DO_G	0.8474	0.0169	58.60	0.8459	0.0165	59.69	0.8239	0.0231	56.91

SIC 382: Measuring and Controlling Devices.										
Year		1992 (n = 1,384)			1997 (n = 1,540)			2002 (n = 1,201)		
		mean	std dev	%>mean	mean	std dev	%>mean	mean	std dev	%>mean
Manufacturing Dominance										
Concentratio Ratio	DM_C	0.3909	0.1184	42.56	0.3975	0.1248	42.01	0.4214	0.1168	42.30
Herfindahl-Hirschman	DM_H	0.0317	0.0492	29.77	0.0324	0.0419	25.58	0.0400	0.0568	28.31
Rosenbluth	DM_R	0.0025	0.0016	41.33	0.0027	0.0022	37.34	0.0030	0.0026	35.89
Gini	DM_G	0.8903	0.0268	45.66	0.8987	0.0254	43.51	0.8967	0.0248	41.72
Economy-Wide Dominance										
Concentratio Ratio	DO_C	0.1215	0.0326	45.38	0.1129	0.0262	40.97	0.1160	0.0293	36.89
Herfindahl-Hirschman	DO_H	0.0020	0.0013	35.55	0.0016	0.0008	38.51	0.0017	0.0009	36.89
Rosenbluth	DO_R	0.0001	0.0001	47.83	0.0001	0.0001	39.03	0.0001	0.0001	42.55
Gini	DO_G	0.8546	0.0115	67.92	0.8550	0.0108	58.70	0.8386	0.0157	58.37

Table A.10.2. Parameter Estimates with Economy-Wide Dominance Controls for Rubber and Plastics (SIC 30).

		Base Model				Manufacturing Dominance				Overall Dominance			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
1992													
D_C	γ_d	-0.0447	0.0389	-1.15	0.25	-0.0361	0.0399	-0.90	0.37	-0.0255	0.0423	-0.60	0.55
	τ					-0.0343	0.0349	-0.98	0.33	-0.1623	0.1402	-1.16	0.25
D_H	γ_d	-0.1616	0.1119	-1.44	0.15	-0.1509	0.1122	-1.34	0.18	-0.1555	0.1180	-1.32	0.19
	τ					-0.0804	0.0627	-1.28	0.20	-0.4396	2.7119	-0.16	0.87
D_R	γ_d	-0.9101	0.2383	-3.82	0.00	-0.6390	0.2851	-2.24	0.03	-0.6595	0.2607	-2.53	0.01
	τ					-1.9654	1.1372	-1.73	0.08	-70.6891	29.9143	-2.36	0.02
D_G	γ_d	0.3673	0.0832	4.41	0.00	0.3672	0.0832	4.41	0.00	0.3685	0.0832	4.43	0.00
	τ					0.0263	0.1487	0.18	0.86	1.2539	0.3654	3.43	0.00
1997													
D_C	γ_d	-0.0510	0.0332	-1.53	0.12	-0.0616	0.0341	-1.81	0.07	-0.0524	0.0355	-1.47	0.14
	τ					0.0382	0.0281	1.36	0.17	0.0149	0.1387	0.11	0.91
D_H	γ_d	-0.0457	0.0856	-0.53	0.59	-0.0387	0.0860	-0.45	0.65	-0.0369	0.0894	-0.41	0.68
	τ					-0.0515	0.0618	-0.83	0.40	-0.9819	2.8585	-0.34	0.73
D_R	γ_d	-0.5765	0.1863	-3.09	0.00	-0.5490	0.1996	-2.75	0.01	-0.3216	0.2052	-1.57	0.12
	τ					-0.3124	0.8114	-0.38	0.70	-79.6381	26.8141	-2.97	0.00
D_G	γ_d	0.3341	0.0741	4.51	0.00	0.3182	0.0748	4.25	0.00	0.3279	0.0741	4.42	0.00
	τ					0.1960	0.1262	1.55	0.12	0.8858	0.3016	2.94	0.00
2002													
D_C	γ_d	-0.0653	0.0369	-1.77	0.08	-0.0711	0.0378	-1.88	0.06	-0.0546	0.0381	-1.43	0.15
	τ					0.0216	0.0310	0.70	0.48	-0.1438	0.1318	-1.09	0.28
D_H	γ_d	-0.4631	0.1047	-4.42	0.00	-0.4717	0.1056	-4.46	0.00	-0.4333	0.1070	-4.05	0.00
	τ					0.0377	0.0629	0.60	0.55	-2.4466	1.8113	-1.35	0.18
D_R	γ_d	-1.0107	0.1676	-6.03	0.00	-1.0122	0.1904	-5.32	0.00	-0.9302	0.1767	-5.27	0.00
	τ					0.0130	0.7960	0.02	0.99	-31.9736	22.1891	-1.44	0.15
D_G	γ_d	0.3499	0.0868	4.03	0.00	0.3367	0.0876	3.85	0.00	0.3553	0.0868	4.09	0.00
	τ					0.1619	0.1394	1.16	0.25	0.9286	0.2783	3.34	0.00

Note: τ indicates the regional manufacturing dominance or overall regional dominance control variable.

Table A.10.3. Parameter Estimates with Economy-Wide Dominance Controls for Metalworking Machinery (SIC 354).

		Base Model				Manufacturing Dominance				Overall Dominance			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
1992													
D_C	γ_d	-0.0875	0.0413	-2.12	0.03	-0.0928	0.0419	-2.22	0.03	-0.0899	0.0414	-2.17	0.03
	τ					-0.0323	0.0421	-0.77	0.44	-0.2251	0.1915	-1.18	0.24
D_H	γ_d	-0.1121	0.1055	-1.06	0.29	-0.1175	0.1058	-1.11	0.27	-0.1175	0.1063	-1.11	0.27
	τ					-0.0651	0.0883	-0.74	0.46	-1.3255	3.2463	-0.41	0.68
D_R	γ_d	-0.2563	0.2254	-1.14	0.26	0.0644	0.2380	0.27	0.79	-0.0142	0.2304	-0.06	0.95
	τ					-5.3770	1.2941	-4.15	0.00	-133.7777	27.2244	-4.91	0.00
D_G	γ_d	0.2912	0.0895	3.25	0.00	0.2924	0.0895	3.27	0.00	0.2729	0.0911	3.00	0.00
	τ					0.2642	0.1560	1.69	0.09	0.4635	0.4302	1.08	0.28
1997													
D_C	γ_d	-0.2001	0.0407	-4.91	0.00	-0.2050	0.0415	-4.94	0.00	-0.1977	0.0407	-4.85	0.00
	τ					-0.0251	0.0402	-0.62	0.53	-0.5628	0.2072	-2.72	0.01
D_H	γ_d	-0.1830	0.0796	-2.30	0.02	-0.1829	0.0796	-2.30	0.02	-0.1695	0.0804	-2.11	0.03
	τ					-0.0030	0.0806	-0.04	0.97	-4.7396	3.8558	-1.23	0.22
D_R	γ_d	-0.6614	0.1731	-3.82	0.00	-0.5371	0.1784	-3.01	0.00	-0.5420	0.1754	-3.09	0.00
	τ					-3.7020	1.2986	-2.85	0.00	-93.3752	23.1525	-4.03	0.00
D_G	γ_d	0.2169	0.0775	2.80	0.01	0.1924	0.0777	2.48	0.01	0.1342	0.0793	1.69	0.09
	τ					0.5794	0.1665	3.48	0.00	1.9566	0.4193	4.67	0.00
2002													
D_C	γ_d	-0.1900	0.0518	-3.67	0.00	-0.1784	0.0521	-3.43	0.00	-0.1839	0.0518	-3.55	0.00
	τ					0.0918	0.0458	2.01	0.04	-0.6096	0.2733	-2.23	0.03
D_H	γ_d	-0.2661	0.1012	-2.63	0.01	-0.2287	0.1014	-2.26	0.02	-0.2626	0.1012	-2.60	0.01
	τ					0.4084	0.1037	3.94	0.00	-5.4188	4.2631	-1.27	0.20
D_R	γ_d	-0.7175	0.1757	-4.08	0.00	-0.7103	0.1760	-4.04	0.00	-0.6172	0.1763	-3.50	0.00
	τ					-0.9185	1.2426	-0.74	0.46	-143.2220	28.1862	-5.08	0.00
D_G	γ_d	0.3920	0.1000	3.92	0.00	0.3540	0.1003	3.53	0.00	0.3840	0.1004	3.82	0.00
	τ					0.7658	0.2020	3.79	0.00	0.3623	0.4031	0.90	0.37

Note: τ indicates the regional manufacturing dominance or overall regional dominance control variable.

Table A.10.4. Parameter Estimates with Economy-Wide Dominance Controls for Measuring and Controlling Devices (SIC 382).

		Base Model				Manufacturing Dominance				Overall Dominance			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
1992													
D_C	γ_d	-0.3532	0.1832	-1.93	0.05	-0.3792	0.1836	-2.07	0.04	-0.3136	0.1835	-1.71	0.09
	τ					-0.2859	0.1616	-1.77	0.08	-2.1023	0.8862	-2.37	0.02
D_H	γ_d	-0.6369	0.2724	-2.34	0.02	-0.6800	0.3171	-2.14	0.03	-0.2864	0.2986	-0.96	0.34
	τ					0.0722	0.2760	0.26	0.79	-52.3674	18.6142	-2.81	0.00
D_R	γ_d	-2.0502	0.6850	-2.99	0.00	-2.0364	0.6857	-2.97	0.00	-2.0334	0.6866	-2.96	0.00
	τ					-8.1894	13.9361	-0.59	0.56	-135.0667	343.1008	-0.39	0.69
D_G	γ_d	0.4963	0.3390	1.46	0.14	0.5506	0.3405	1.62	0.11	0.4554	0.3701	1.23	0.22
	τ					-0.7569	0.5022	-1.51	0.13	0.4421	1.6112	0.27	0.78
1997													
D_C	γ_d	-0.2499	0.1441	-1.73	0.08	-0.3222	0.1469	-2.19	0.03	-0.2718	0.1448	-1.88	0.06
	τ					-0.3200	0.1322	-2.42	0.02	-1.0739	0.7329	-1.47	0.14
D_H	γ_d	-0.1969	0.2141	-0.92	0.36	-0.1903	0.2199	-0.87	0.39	-0.1921	0.2142	-0.90	0.37
	τ					-0.0357	0.2688	-0.13	0.89	-14.5603	20.3077	-0.72	0.47
D_R	γ_d	-1.8161	0.6050	-3.00	0.00	-1.8215	0.6051	-3.01	0.00	-1.5870	0.6254	-2.54	0.01
	τ					-4.8748	6.7612	-0.72	0.47	-494.9902	345.2949	-1.43	0.15
D_G	γ_d	1.1763	0.2813	4.18	0.00	1.1760	0.2814	4.18	0.00	1.0692	0.3037	3.52	0.00
	τ					0.1920	0.4836	0.40	0.69	1.2329	1.3161	0.94	0.35
2002													
D_C	γ_d	0.1184	0.1793	0.66	0.51	0.0382	0.1830	0.21	0.83	0.1258	0.1798	0.70	0.48
	τ					-0.2796	0.1312	-2.13	0.03	-0.4260	0.7569	-0.56	0.57
D_H	γ_d	0.5532	0.2702	2.05	0.04	0.5426	0.2749	1.97	0.05	0.5663	0.2745	2.06	0.04
	τ					-0.0478	0.2299	-0.21	0.84	-5.3943	19.5346	-0.28	0.78
D_R	γ_d	0.0582	0.5339	0.11	0.91	-0.0668	0.5448	-0.12	0.90	0.0462	0.5345	0.09	0.93
	τ					-6.9670	5.9418	-1.17	0.24	-274.0474	383.9616	-0.71	0.48
D_G	γ_d	0.4634	0.3075	1.51	0.13	0.4584	0.3075	1.49	0.14	0.5198	0.3170	1.64	0.10
	τ					-0.7632	0.6090	-1.25	0.21	-0.8769	1.1834	-0.74	0.46

Note: τ indicates the regional manufacturing dominance or overall regional dominance control variable.

Appendix 11. Plant Size Interactions

Table A.11.1 through A.11.9 present the coefficient estimates, standard errors, t-statistics, and probability values for the marginal impacts obtained by re-evaluating the four-equation production and cost share system partitioned by absolute and relative plant size categories, using the four measures of regional industrial dominance.

Table A.11.1. Marginal Impacts Including Plant Size Interactions for Rubber and Plastics (SIC 30), 1992.

		Dominance Categories				Small ≤ 250 Employees				Small ≤ 50 Employees				Small ≤ 15 Employees			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
Concentration Ratio Dominance (D_C)																	
Dominators		0.1389	0.0171	8.14	0.00												
Dominated / Small		-0.1879	0.0116	-16.19	0.00	-0.0415	0.0209	-1.98	0.05	0.0034	0.0119	0.29	0.77	0.0752	0.0132	5.71	0.00
Dominance	dominator	0.1274	0.0686	1.86	0.06												
	neither / large	-0.0923	0.0457	-2.02	0.04	0.2187	0.1028	2.13	0.03	0.0056	0.0498	0.11	0.91	-0.0154	0.0421	-0.37	0.71
	dominated / small	-0.0225	0.0546	-0.41	0.68	-0.0480	0.0409	-1.17	0.24	-0.0531	0.0463	-1.15	0.25	-0.1001	0.0667	-1.50	0.13
Labor	dominator	-0.3656	1.3993	-0.26	0.79												
Pooling	neither / large	0.8273	0.7739	1.07	0.29	0.0902	2.0237	0.04	0.96	1.0326	0.8463	1.22	0.22	1.2888	0.6561	1.96	0.05
	dominated / small	1.3223	0.8186	1.62	0.11	1.1143	0.6233	1.79	0.07	1.1678	0.7253	1.61	0.11	0.1987	1.1220	0.18	0.86
Manufactured	dominator	0.0342	0.0327	1.05	0.30												
Inputs	neither / large	0.0241	0.0175	1.38	0.17	0.0319	0.0478	0.67	0.50	-0.0066	0.0194	-0.34	0.73	-0.0162	0.0144	-1.12	0.26
	dominated / small	-0.0113	0.0165	-0.69	0.49	-0.0142	0.0134	-1.05	0.29	-0.0168	0.0152	-1.11	0.27	-0.0041	0.0221	-0.18	0.85
Producer	dominator	-0.0157	0.0258	-0.61	0.54												
Services	neither / large	-0.0120	0.0152	-0.79	0.43	-0.0087	0.0380	-0.23	0.82	0.0075	0.0162	0.46	0.65	0.0073	0.0130	0.56	0.57
	dominated / small	0.0035	0.0156	0.22	0.82	0.0053	0.0125	0.42	0.67	0.0055	0.0143	0.38	0.70	-0.0048	0.0210	-0.23	0.82
Research	dominator	-0.0080	0.0182	-0.44	0.66												
	neither / large	-0.0058	0.0110	-0.53	0.60	-0.0167	0.0252	-0.66	0.51	-0.0013	0.0120	-0.11	0.91	0.0023	0.0098	0.23	0.81
	dominated / small	0.0093	0.0111	0.84	0.40	0.0014	0.0094	0.15	0.88	0.0017	0.0102	0.17	0.87	-0.0014	0.0136	-0.10	0.92
Patents	dominator	0.0279	0.0231	1.21	0.23												
	neither / large	-0.0201	0.0151	-1.33	0.18	0.0144	0.0351	0.41	0.68	-0.0107	0.0162	-0.66	0.51	-0.0066	0.0133	-0.50	0.62
	dominated / small	0.0167	0.0160	1.04	0.30	-0.0083	0.0127	-0.66	0.51	-0.0047	0.0143	-0.33	0.74	-0.0093	0.0205	-0.46	0.65
Herfindahl-Hirschman Dominance (D_H)																	
Dominators		0.1518	0.0157	9.65	0.00												
Dominated / Small		-0.1943	0.0100	-19.40	0.00	-0.0555	0.0184	-3.02	0.00	-0.0033	0.0108	-0.31	0.76	0.0632	0.0118	5.36	0.00
Dominance	dominator	0.3673	0.2122	1.73	0.08												
	neither / large	-0.2501	0.1383	-1.81	0.07	0.6442	0.3455	1.86	0.06	0.0594	0.1593	0.37	0.71	-0.0109	0.1261	-0.09	0.93
	dominated / small	-0.1740	0.1881	-0.93	0.35	-0.1201	0.1200	-1.00	0.32	-0.1387	0.1421	-0.98	0.33	-0.2822	0.2312	-1.22	0.22
Labor	dominator	-0.6206	1.4108	-0.44	0.66												
Pooling	neither / large	0.9091	0.7542	1.21	0.23	-0.0833	2.0735	-0.04	0.97	1.1427	0.8260	1.38	0.17	1.4759	0.6178	2.39	0.02
	dominated / small	1.4926	0.7818	1.91	0.06	1.3332	0.5810	2.29	0.02	1.3970	0.6894	2.03	0.04	0.4990	1.1073	0.45	0.65
Manufactured	dominator	0.0403	0.0327	1.23	0.22												
Inputs	neither / large	0.0329	0.0173	1.90	0.06	0.0346	0.0478	0.72	0.47	-0.0032	0.0191	-0.17	0.87	-0.0121	0.0141	-0.86	0.39
	dominated / small	-0.0054	0.0163	-0.33	0.74	-0.0104	0.0131	-0.79	0.43	-0.0135	0.0149	-0.91	0.36	0.0006	0.0220	0.03	0.98
Producer	dominator	-0.0227	0.0258	-0.88	0.38												
Services	neither / large	-0.0164	0.0149	-1.10	0.27	-0.0137	0.0379	-0.36	0.72	0.0064	0.0159	0.41	0.68	0.0070	0.0125	0.56	0.57
	dominated / small	-0.0017	0.0150	-0.11	0.91	0.0065	0.0120	0.54	0.59	0.0069	0.0138	0.50	0.62	-0.0003	0.0206	-0.02	0.99
Research	dominator	-0.0060	0.0180	-0.33	0.74												
	neither / large	-0.0063	0.0106	-0.59	0.56	-0.0149	0.0248	-0.60	0.55	-0.0014	0.0116	-0.12	0.90	0.0017	0.0093	0.18	0.86
	dominated / small	0.0080	0.0106	0.76	0.45	-0.0001	0.0088	-0.01	0.99	-0.0003	0.0096	-0.03	0.98	-0.0061	0.0131	-0.46	0.64
Patents	dominator	0.0174	0.0226	0.77	0.44												
	neither / large	-0.0251	0.0138	-1.82	0.07	0.0065	0.0339	0.19	0.85	-0.0095	0.0148	-0.64	0.52	-0.0051	0.0118	-0.43	0.67
	dominated / small	0.0102	0.0147	0.69	0.49	-0.0053	0.0112	-0.47	0.64	-0.0011	0.0129	-0.09	0.93	-0.0012	0.0195	-0.06	0.95

Note: "Neither" and "dominated" label the dominance models, "large" and "small" pertain to the small establishment models.

Table A.11.1. Marginal Impacts Including Plant Size Interactions for Rubber and Plastics (SIC 30), 1992, continued.

		Dominance Categories				Small ≤ 250 Employees				Small ≤ 50 Employees				Small ≤ 15 Employees			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
Rosenbluth Dominance (D_R)																	
Dominators		0.1443	0.0164	8.82	0.00												
Dominated / Small		-0.1993	0.0102	-19.59	0.00	-0.0528	0.0185	-2.85	0.00	-0.0041	0.0109	-0.38	0.70	0.0593	0.0120	4.96	0.00
Dominance	dominator	-0.0711	0.3425	-0.21	0.84												
	neither / large	-0.9726	0.2888	-3.37	0.00	0.5664	0.6325	0.90	0.37	-0.1621	0.3241	-0.50	0.62	-0.2769	0.2748	-1.01	0.31
	dominated / small	-1.3400	0.4200	-3.19	0.00	-0.5326	0.2721	-1.96	0.05	-0.6561	0.3062	-2.14	0.03	-1.3928	0.4743	-2.94	0.00
Labor	dominator	0.0099	1.4108	0.01	0.99												
Pooling	neither / large	0.7811	0.7554	1.03	0.30	0.7921	2.0735	0.38	0.70	1.2039	0.8266	1.46	0.15	1.4765	0.6218	2.37	0.02
	dominated / small	1.3330	0.7840	1.70	0.09	1.2901	0.5863	2.20	0.03	1.3483	0.6943	1.94	0.05	0.5153	1.1073	0.47	0.64
Manufactured	dominator	0.0272	0.0327	0.83	0.41												
Inputs	neither / large	0.0284	0.0173	1.64	0.10	0.0225	0.0476	0.47	0.64	-0.0059	0.0191	-0.31	0.76	-0.0146	0.0142	-1.04	0.30
	dominated / small	-0.0112	0.0162	-0.69	0.49	-0.0127	0.0132	-0.96	0.34	-0.0160	0.0149	-1.07	0.28	-0.0047	0.0219	-0.22	0.83
Producer	dominator	-0.0080	0.0260	-0.31	0.76												
Services	neither / large	-0.0113	0.0151	-0.75	0.46	0.0015	0.0384	0.04	0.97	0.0117	0.0161	0.72	0.47	0.0117	0.0127	0.92	0.36
	dominated / small	-0.0008	0.0153	-0.05	0.96	0.0083	0.0122	0.68	0.50	0.0071	0.0141	0.51	0.61	-0.0053	0.0209	-0.25	0.80
Research	dominator	-0.0071	0.0181	-0.39	0.70												
	neither / large	-0.0060	0.0107	-0.56	0.58	-0.0177	0.0251	-0.70	0.48	-0.0024	0.0117	-0.21	0.84	0.0010	0.0094	0.11	0.91
	dominated / small	0.0113	0.0108	1.05	0.29	0.0004	0.0089	0.05	0.96	0.0012	0.0098	0.12	0.91	-0.0012	0.0133	-0.09	0.93
Patents	dominator	0.0174	0.0230	0.76	0.45												
	neither / large	-0.0258	0.0144	-1.80	0.07	0.0097	0.0353	0.27	0.78	-0.0080	0.0155	-0.51	0.61	-0.0036	0.0124	-0.29	0.77
	dominated / small	0.0015	0.0154	0.10	0.92	-0.0065	0.0117	-0.56	0.58	-0.0049	0.0135	-0.36	0.72	-0.0142	0.0201	-0.71	0.48
Gini Dominance (D_G)																	
Dominators		0.1483	0.0152	9.77	0.00												
Dominated / Small		-0.1911	0.0106	-17.99	0.00	-0.0419	0.0196	-2.14	0.03	-0.0029	0.0111	-0.26	0.80	0.0627	0.0122	5.16	0.00
Dominance	dominator	0.8050	0.1842	4.37	0.00												
	neither / large	0.2107	0.1069	1.97	0.05	0.7202	0.2912	2.47	0.01	0.2899	0.1183	2.45	0.01	0.1308	0.0904	1.45	0.15
	dominated / small	0.3748	0.1260	2.98	0.00	0.0776	0.0865	0.90	0.37	0.0061	0.1032	0.06	0.95	0.0850	0.1662	0.51	0.61
Labor	dominator	-0.1548	1.3895	-0.11	0.91												
Pooling	neither / large	0.6749	0.7447	0.91	0.36	0.4029	1.9943	0.20	0.84	0.9470	0.8109	1.17	0.24	1.1836	0.6022	1.97	0.05
	dominated / small	1.7644	0.7672	2.30	0.02	0.9419	0.5644	1.67	0.10	0.9376	0.6732	1.39	0.16	-0.1297	1.0975	-0.12	0.91
Manufactured	dominator	0.0301	0.0324	0.93	0.35												
Inputs	neither / large	0.0359	0.0173	2.07	0.04	0.0200	0.0468	0.43	0.67	-0.0038	0.0191	-0.20	0.84	-0.0117	0.0141	-0.83	0.41
	dominated / small	-0.0075	0.0162	-0.46	0.65	-0.0071	0.0132	-0.54	0.59	-0.0085	0.0149	-0.57	0.57	0.0070	0.0218	0.32	0.75
Producer	dominator	-0.0244	0.0257	-0.95	0.34												
Services	neither / large	-0.0165	0.0150	-1.11	0.27	-0.0160	0.0378	-0.42	0.67	0.0042	0.0160	0.26	0.79	0.0045	0.0126	0.36	0.72
	dominated / small	0.0044	0.0152	0.29	0.77	0.0046	0.0121	0.38	0.70	0.0044	0.0139	0.32	0.75	-0.0013	0.0206	-0.06	0.95
Research	dominator	0.0048	0.0178	0.27	0.79												
	neither / large	-0.0025	0.0106	-0.24	0.81	-0.0013	0.0249	-0.05	0.96	0.0035	0.0116	0.30	0.76	0.0048	0.0093	0.52	0.61
	dominated / small	0.0133	0.0107	1.24	0.22	0.0010	0.0088	0.12	0.91	-0.0007	0.0096	-0.07	0.95	-0.0066	0.0132	-0.50	0.61
Patents	dominator	0.0075	0.0216	0.35	0.73												
	neither / large	-0.0221	0.0130	-1.70	0.09	-0.0153	0.0317	-0.48	0.63	-0.0143	0.0140	-1.02	0.31	-0.0082	0.0110	-0.75	0.46
	dominated / small	0.0075	0.0137	0.55	0.58	-0.0048	0.0105	-0.46	0.65	0.0002	0.0121	0.02	0.98	0.0071	0.0183	0.39	0.70

Note: "Neither" and "dominated" label the dominance models, "large" and "small" pertain to the small establishment models.

Table A.11.2. Marginal Impacts Including Plant Size Interactions for Rubber and Plastics (SIC 30), 1997.

		Dominance Categories				Small ≤ 250 Employees				Small ≤ 50 Employees				Small ≤ 15 Employees			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
Concentration Ratio Dominance (D_C)																	
Dominators		0.1524	0.0153	9.95	0.00												
Dominated / Small		-0.1783	0.0107	-16.66	0.00	-0.0643	0.0190	-3.38	0.00	0.0084	0.0107	0.78	0.43	0.0758	0.0124	6.13	0.00
Dominance	dominator	-0.0641	0.0553	-1.16	0.25												
	neither / large	-0.1249	0.0402	-3.11	0.00	0.0800	0.0852	0.94	0.35	0.0103	0.0423	0.24	0.81	0.0175	0.0358	0.49	0.62
	dominated / small	0.0166	0.0466	0.36	0.72	0.0197	0.0347	0.57	0.57	0.0333	0.0395	0.84	0.40	0.0189	0.0559	0.34	0.74
Labor	dominator	-1.0979	0.5820	-1.89	0.06												
Pooling	neither / large	-0.2573	0.3852	-0.67	0.50	-0.8546	0.7782	-1.10	0.27	-0.2714	0.3959	-0.69	0.49	-0.3765	0.3459	-1.09	0.28
	dominated / small	0.4773	0.4005	1.19	0.23	-0.2565	0.3365	-0.76	0.45	-0.2469	0.3754	-0.66	0.51	0.0641	0.5108	0.13	0.90
Manufactured	dominator	0.0229	0.0221	1.04	0.30												
Inputs	neither / large	0.0098	0.0145	0.67	0.50	-0.0322	0.0329	-0.98	0.33	-0.0142	0.0152	-0.93	0.35	0.0022	0.0122	0.18	0.86
	dominated / small	-0.0080	0.0144	-0.56	0.58	0.0053	0.0116	0.45	0.65	0.0139	0.0131	1.07	0.29	0.0080	0.0189	0.43	0.67
Producer	dominator	-0.0062	0.0221	-0.28	0.78												
Services	neither / large	-0.0174	0.0152	-1.15	0.25	-0.0035	0.0328	-0.11	0.92	0.0039	0.0157	0.25	0.80	-0.0027	0.0129	-0.21	0.84
	dominated / small	0.0120	0.0154	0.78	0.44	-0.0007	0.0123	-0.06	0.95	-0.0023	0.0140	-0.17	0.87	0.0052	0.0201	0.26	0.79
Research	dominator	0.0096	0.0133	0.72	0.47												
	neither / large	0.0189	0.0083	2.28	0.02	0.0097	0.0206	0.47	0.64	0.0088	0.0092	0.95	0.34	-0.0015	0.0073	-0.20	0.84
	dominated / small	-0.0031	0.0086	-0.36	0.72	-0.0043	0.0068	-0.63	0.53	-0.0127	0.0075	-1.71	0.09	-0.0159	0.0100	-1.60	0.11
Patents	dominator	0.0089	0.0179	0.50	0.62												
	neither / large	0.0067	0.0124	0.54	0.59	0.0685	0.0272	2.52	0.01	0.0043	0.0128	0.33	0.74	0.0086	0.0107	0.81	0.42
	dominated / small	0.0342	0.0128	2.68	0.01	0.0048	0.0103	0.46	0.64	0.0109	0.0116	0.94	0.35	0.0027	0.0166	0.16	0.87
Herfindahl-Hirschman Dominance (D_H)																	
Dominators		0.1509	0.0135	11.15	0.00												
Dominated / Small		-0.1765	0.0095	-18.61	0.00	-0.0728	0.0165	-4.40	0.00	0.0008	0.0097	0.08	0.94	0.0729	0.0117	6.24	0.00
Dominance	dominator	-0.0302	0.1543	-0.20	0.84												
	neither / large	-0.1488	0.1116	-1.33	0.18	0.4303	0.2811	1.53	0.13	0.1623	0.1271	1.28	0.20	0.1263	0.0972	1.30	0.19
	dominated / small	0.1501	0.1724	0.87	0.38	0.1313	0.0919	1.43	0.15	0.1475	0.1075	1.37	0.17	-0.0434	0.2019	-0.21	0.83
Labor	dominator	-1.0317	0.5811	-1.78	0.08												
Pooling	neither / large	-0.1055	0.3796	-0.28	0.78	-0.6978	0.7799	-0.89	0.37	-0.2470	0.3877	-0.64	0.52	-0.2789	0.3370	-0.83	0.41
	dominated / small	0.6070	0.3937	1.54	0.12	-0.1828	0.3266	-0.56	0.58	-0.1864	0.3664	-0.51	0.61	0.1112	0.5052	0.22	0.83
Manufactured	dominator	0.0215	0.0222	0.96	0.33												
Inputs	neither / large	0.0081	0.0143	0.57	0.57	-0.0397	0.0336	-1.18	0.24	-0.0149	0.0150	-0.99	0.32	0.0007	0.0119	0.06	0.96
	dominated / small	-0.0098	0.0141	-0.70	0.48	0.0039	0.0112	0.35	0.73	0.0117	0.0128	0.92	0.36	0.0063	0.0189	0.34	0.74
Producer	dominator	-0.0030	0.0221	-0.14	0.89												
Services	neither / large	-0.0106	0.0150	-0.71	0.48	0.0067	0.0331	0.20	0.84	0.0067	0.0155	0.43	0.66	0.0013	0.0126	0.11	0.92
	dominated / small	0.0130	0.0152	0.86	0.39	0.0025	0.0121	0.21	0.83	0.0007	0.0138	0.05	0.96	0.0058	0.0201	0.29	0.77
Research	dominator	0.0104	0.0132	0.78	0.43												
	neither / large	0.0195	0.0081	2.41	0.02	0.0111	0.0203	0.55	0.58	0.0102	0.0089	1.15	0.25	-0.0014	0.0070	-0.20	0.84
	dominated / small	-0.0017	0.0083	-0.20	0.84	-0.0040	0.0064	-0.63	0.53	-0.0124	0.0071	-1.75	0.08	-0.0135	0.0097	-1.40	0.16
Patents	dominator	0.0116	0.0172	0.67	0.50												
	neither / large	0.0127	0.0116	1.10	0.27	0.0787	0.0264	2.99	0.00	0.0130	0.0118	1.09	0.27	0.0159	0.0097	1.64	0.10
	dominated / small	0.0349	0.0119	2.93	0.00	0.0111	0.0093	1.20	0.23	0.0170	0.0108	1.58	0.11	0.0052	0.0162	0.32	0.75

Note: "Neither" and "dominated" label the dominance models, "large" and "small" pertain to the small establishment models.

Table A.11.2. Marginal Impacts Including Plant Size Interactions for Rubber and Plastics (SIC 30), 1997, continued.

		Dominance Categories				Small ≤ 250 Employees				Small ≤ 50 Employees				Small ≤ 15 Employees			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
Rosenbluth Dominance (D_R)																	
Dominators		0.1602	0.0154	10.42	0.00												
Dominated / Small		-0.1770	0.0096	-18.39	0.00	-0.0592	0.0172	-3.45	0.00	0.0052	0.0100	0.52	0.60	0.0823	0.0116	7.10	0.00
Dominance	dominator	-0.4368	0.2556	-1.71	0.09												
	neither / large	-0.9643	0.2461	-3.92	0.00	-0.2178	0.5100	-0.43	0.67	0.1091	0.2602	0.42	0.68	0.1846	0.2214	0.83	0.40
	dominated / small	-0.1383	0.3327	-0.42	0.68	0.2456	0.2173	1.13	0.26	0.2544	0.2490	1.02	0.31	0.1854	0.3615	0.51	0.61
Labor	dominator	-1.1325	0.5797	-1.95	0.05												
Pooling	neither / large	-0.2014	0.3804	-0.53	0.60	-0.9372	0.7628	-1.23	0.22	-0.2174	0.3908	-0.56	0.58	-0.2942	0.3416	-0.86	0.39
	dominated / small	0.4180	0.3959	1.06	0.29	-0.1990	0.3328	-0.60	0.55	-0.1971	0.3719	-0.53	0.60	0.1171	0.5078	0.23	0.82
Manufactured	dominator	0.0245	0.0220	1.11	0.27												
Inputs	neither / large	0.0088	0.0140	0.63	0.53	-0.0235	0.0327	-0.72	0.47	-0.0163	0.0147	-1.11	0.27	-0.0015	0.0116	-0.13	0.90
	dominated / small	-0.0086	0.0138	-0.63	0.53	0.0023	0.0110	0.21	0.83	0.0113	0.0125	0.90	0.37	0.0072	0.0185	0.39	0.70
Producer	dominator	-0.0066	0.0220	-0.30	0.76												
Services	neither / large	-0.0156	0.0149	-1.04	0.30	-0.0142	0.0322	-0.44	0.66	0.0064	0.0155	0.42	0.68	0.0011	0.0127	0.09	0.93
	dominated / small	0.0123	0.0151	0.81	0.42	0.0029	0.0121	0.24	0.81	-0.0001	0.0138	0.00	1.00	0.0067	0.0201	0.33	0.74
Research	dominator	0.0108	0.0132	0.81	0.42												
	neither / large	0.0206	0.0081	2.54	0.01	0.0125	0.0205	0.61	0.54	0.0105	0.0090	1.16	0.25	-0.0006	0.0071	-0.08	0.93
	dominated / small	-0.0028	0.0084	-0.33	0.74	-0.0033	0.0066	-0.50	0.62	-0.0120	0.0072	-1.66	0.10	-0.0143	0.0098	-1.45	0.15
Patents	dominator	0.0082	0.0180	0.45	0.65												
	neither / large	0.0062	0.0119	0.53	0.60	0.0549	0.0280	1.96	0.05	0.0100	0.0123	0.82	0.41	0.0148	0.0100	1.49	0.14
	dominated / small	0.0363	0.0121	3.00	0.00	0.0110	0.0095	1.16	0.25	0.0160	0.0110	1.45	0.15	0.0076	0.0163	0.46	0.64
Gini Dominance (D_G)																	
Dominators		0.1326	0.0134	9.88	0.00												
Dominated / Small		-0.1862	0.0095	-19.51	0.00	-0.0759	0.0172	-4.41	0.00	-0.0054	0.0098	-0.56	0.58	0.0732	0.0111	6.60	0.00
Dominance	dominator	0.3640	0.1575	2.31	0.02												
	neither / large	0.2215	0.0964	2.30	0.02	0.6902	0.2513	2.75	0.01	0.2214	0.1042	2.12	0.03	0.1269	0.0808	1.57	0.12
	dominated / small	0.3598	0.1119	3.22	0.00	0.1266	0.0767	1.65	0.10	0.1349	0.0913	1.48	0.14	0.3144	0.1410	2.23	0.03
Labor	dominator	-0.7789	0.5770	-1.35	0.18												
Pooling	neither / large	0.0923	0.3776	0.24	0.81	-0.8077	0.7816	-1.03	0.30	-0.4652	0.3858	-1.21	0.23	-0.5419	0.3344	-1.62	0.11
	dominated / small	0.6929	0.3937	1.76	0.08	-0.3720	0.3248	-1.15	0.25	-0.3779	0.3627	-1.04	0.30	-0.0678	0.4979	-0.14	0.89
Manufactured	dominator	0.0152	0.0216	0.70	0.48												
Inputs	neither / large	-0.0015	0.0135	-0.11	0.91	-0.0249	0.0326	-0.76	0.44	-0.0123	0.0142	-0.86	0.39	0.0011	0.0111	0.10	0.92
	dominated / small	-0.0094	0.0136	-0.69	0.49	0.0048	0.0104	0.46	0.64	0.0121	0.0121	1.00	0.32	0.0044	0.0180	0.24	0.81
Producer	dominator	0.0059	0.0210	0.28	0.78												
Services	neither / large	-0.0016	0.0140	-0.11	0.91	-0.0072	0.0310	-0.23	0.82	0.0015	0.0146	0.10	0.92	-0.0032	0.0119	-0.27	0.79
	dominated / small	0.0136	0.0145	0.94	0.35	0.0005	0.0113	0.04	0.97	-0.0007	0.0129	-0.05	0.96	0.0113	0.0188	0.60	0.55
Research	dominator	0.0079	0.0132	0.60	0.55												
	neither / large	0.0234	0.0080	2.93	0.00	0.0181	0.0202	0.90	0.37	0.0135	0.0088	1.53	0.13	0.0022	0.0069	0.31	0.75
	dominated / small	0.0018	0.0083	0.22	0.83	-0.0026	0.0064	-0.41	0.68	-0.0112	0.0071	-1.59	0.11	-0.0117	0.0098	-1.20	0.23
Patents	dominator	0.0090	0.0173	0.52	0.60												
	neither / large	0.0094	0.0111	0.84	0.40	0.0485	0.0257	1.89	0.06	0.0094	0.0114	0.82	0.41	0.0167	0.0093	1.80	0.07
	dominated / small	0.0206	0.0114	1.81	0.07	0.0133	0.0089	1.50	0.13	0.0200	0.0104	1.93	0.05	0.0149	0.0154	0.97	0.33

Note: "Neither" and "dominated" label the dominance models, "large" and "small" pertain to the small establishment models.

Table A.11.3. Marginal Impacts Including Plant Size Interactions for Rubber and Plastics (SIC 30), 2002.

		Dominance Categories				Small ≤ 250 Employees				Small ≤ 50 Employees				Small ≤ 15 Employees			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
Concentration Ratio Dominance (D_C)																	
Dominators		0.2073	0.0165	12.60	0.00												
Dominated / Small		-0.1695	0.0128	-13.25	0.00	-0.1221	0.0224	-5.45	0.00	-0.0030	0.0127	-0.24	0.81	0.1367	0.0155	8.82	0.00
Dominance	dominator	0.0245	0.0597	0.41	0.68												
	neither / large	-0.1484	0.0439	-3.38	0.00	0.3485	0.0942	3.70	0.00	0.0767	0.0470	1.63	0.10	0.0525	0.0392	1.34	0.18
	dominated / small	0.0188	0.0612	0.31	0.76	0.0143	0.0386	0.37	0.71	0.0164	0.0451	0.36	0.72	0.0184	0.0747	0.25	0.81
Labor	dominator	-0.3009	0.6117	-0.49	0.62												
Pooling	neither / large	1.2067	0.4153	2.91	0.00	-0.5022	0.8354	-0.60	0.55	0.6857	0.4283	1.60	0.11	0.5007	0.3679	1.36	0.17
	dominated / small	0.1340	0.4592	0.29	0.77	0.4252	0.3610	1.18	0.24	0.0571	0.4157	0.14	0.89	-0.5207	0.6198	-0.84	0.40
Manufactured	dominator	0.0199	0.0269	0.74	0.46												
Inputs	neither / large	-0.0124	0.0170	-0.73	0.46	0.0133	0.0423	0.32	0.75	-0.0113	0.0182	-0.62	0.54	-0.0100	0.0142	-0.70	0.48
	dominated / small	-0.0089	0.0180	-0.49	0.62	-0.0126	0.0133	-0.95	0.34	-0.0081	0.0157	-0.52	0.61	-0.0109	0.0250	-0.44	0.66
Producer	dominator	-0.0164	0.0249	-0.66	0.51												
Services	neither / large	0.0293	0.0171	1.71	0.09	0.0119	0.0393	0.30	0.76	0.0243	0.0180	1.35	0.18	0.0210	0.0146	1.44	0.15
	dominated / small	0.0016	0.0192	0.08	0.93	0.0189	0.0141	1.35	0.18	0.0089	0.0166	0.54	0.59	-0.0042	0.0262	-0.16	0.87
Research	dominator	0.0229	0.0164	1.39	0.16												
	neither / large	0.0047	0.0100	0.47	0.64	-0.0340	0.0261	-1.31	0.19	-0.0082	0.0109	-0.75	0.45	-0.0087	0.0089	-0.98	0.32
	dominated / small	0.0038	0.0116	0.33	0.74	-0.0050	0.0085	-0.59	0.56	-0.0051	0.0099	-0.51	0.61	0.0082	0.0152	0.54	0.59
Patents	dominator	0.0192	0.0189	1.02	0.31												
	neither / large	0.0178	0.0134	1.33	0.18	0.1025	0.0293	3.50	0.00	0.0225	0.0140	1.61	0.11	0.0188	0.0119	1.57	0.12
	dominated / small	0.0273	0.0161	1.70	0.09	0.0073	0.0117	0.63	0.53	0.0045	0.0137	0.33	0.74	-0.0041	0.0213	-0.19	0.85
Herfindahl-Hirschman Dominance (D_H)																	
Dominators		0.2266	0.0155	14.58	0.00												
Dominated / Small		-0.1678	0.0114	-14.78	0.00	-0.1388	0.0190	-7.32	0.00	-0.0145	0.0115	-1.26	0.21	0.1277	0.0138	9.25	0.00
Dominance	dominator	0.0360	0.1588	0.23	0.82												
	neither / large	-0.8388	0.1382	-6.07	0.00	0.8419	0.2958	2.85	0.00	0.0622	0.1516	0.41	0.68	-0.0364	0.1205	-0.30	0.76
	dominated / small	-0.3579	0.2504	-1.43	0.15	-0.2024	0.1191	-1.70	0.09	-0.2141	0.1402	-1.53	0.13	-0.3104	0.2435	-1.27	0.20
Labor	dominator	-0.2817	0.6124	-0.46	0.65												
Pooling	neither / large	1.1899	0.4043	2.94	0.00	-0.5632	0.8366	-0.67	0.50	0.5836	0.4166	1.40	0.16	0.4098	0.3543	1.16	0.25
	dominated / small	0.1704	0.4447	0.38	0.70	0.3313	0.3458	0.96	0.34	-0.0449	0.4023	-0.11	0.91	-0.6344	0.6098	-1.04	0.30
Manufactured	dominator	0.0130	0.0270	0.48	0.63												
Inputs	neither / large	-0.0057	0.0168	-0.34	0.73	0.0062	0.0425	0.15	0.88	-0.0106	0.0180	-0.59	0.55	-0.0105	0.0140	-0.75	0.45
	dominated / small	-0.0067	0.0178	-0.38	0.71	-0.0122	0.0131	-0.93	0.35	-0.0077	0.0156	-0.49	0.62	-0.0103	0.0250	-0.41	0.68
Producer	dominator	-0.0161	0.0250	-0.64	0.52												
Services	neither / large	0.0233	0.0168	1.39	0.17	0.0072	0.0396	0.18	0.86	0.0190	0.0178	1.07	0.28	0.0166	0.0143	1.16	0.25
	dominated / small	-0.0022	0.0189	-0.12	0.91	0.0148	0.0137	1.08	0.28	0.0043	0.0162	0.26	0.79	-0.0098	0.0259	-0.38	0.71
Research	dominator	0.0265	0.0164	1.61	0.11												
	neither / large	0.0027	0.0099	0.27	0.78	-0.0276	0.0260	-1.06	0.29	-0.0063	0.0107	-0.59	0.56	-0.0069	0.0087	-0.79	0.43
	dominated / small	0.0019	0.0113	0.16	0.87	-0.0037	0.0083	-0.44	0.66	-0.0046	0.0098	-0.48	0.63	0.0086	0.0150	0.57	0.57
Patents	dominator	0.0167	0.0187	0.89	0.37												
	neither / large	0.0126	0.0128	0.98	0.33	0.0948	0.0290	3.27	0.00	0.0208	0.0134	1.56	0.12	0.0181	0.0112	1.61	0.11
	dominated / small	0.0232	0.0155	1.49	0.13	0.0072	0.0110	0.66	0.51	0.0044	0.0131	0.34	0.74	-0.0040	0.0208	-0.19	0.85

Note: "Neither" and "dominated" label the dominance models, "large" and "small" pertain to the small establishment models.

Table A.11.3. Marginal Impacts Including Plant Size Interactions for Rubber and Plastics (SIC 30), 2002, continued.

		Dominance Categories				Small ≤ 250 Employees				Small ≤ 50 Employees				Small ≤ 15 Employees			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
Rosenbluth Dominance (D_R)																	
Dominators		0.2271	0.0157	14.48	0.00												
Dominated / Small		-0.1753	0.0118	-14.86	0.00	-0.1326	0.0189	-7.03	0.00	-0.0180	0.0114	-1.57	0.12	0.1277	0.0139	9.17	0.00
Dominance	dominator	-0.4432	0.2152	-2.06	0.04												
	neither / large	-1.6250	0.2274	-7.15	0.00	0.9655	0.4040	2.39	0.02	0.1216	0.2294	0.53	0.60	-0.1418	0.1979	-0.72	0.47
	dominated / small	-1.5279	0.4263	-3.58	0.00	-0.3807	0.2029	-1.88	0.06	-0.5725	0.2319	-2.47	0.01	-0.6245	0.3831	-1.63	0.10
Labor	dominator	-0.2854	0.6119	-0.47	0.64												
Pooling	neither / large	1.2125	0.4080	2.97	0.00	-0.5518	0.8306	-0.66	0.51	0.6404	0.4213	1.52	0.13	0.4721	0.3606	1.31	0.19
	dominated / small	0.1627	0.4494	0.36	0.72	0.3959	0.3527	1.12	0.26	0.0263	0.4076	0.06	0.95	-0.5566	0.6127	-0.91	0.36
Manufactured	dominator	0.0109	0.0271	0.40	0.69												
Inputs	neither / large	-0.0174	0.0169	-1.03	0.30	0.0082	0.0423	0.19	0.85	-0.0135	0.0180	-0.75	0.46	-0.0125	0.0141	-0.89	0.37
	dominated / small	-0.0133	0.0178	-0.75	0.46	-0.0154	0.0133	-1.16	0.25	-0.0108	0.0157	-0.69	0.49	-0.0144	0.0251	-0.57	0.57
Producer	dominator	-0.0152	0.0251	-0.60	0.55												
Services	neither / large	0.0310	0.0170	1.82	0.07	0.0100	0.0393	0.25	0.80	0.0257	0.0179	1.44	0.15	0.0204	0.0145	1.41	0.16
	dominated / small	0.0019	0.0190	0.10	0.92	0.0188	0.0139	1.35	0.18	0.0056	0.0164	0.34	0.73	-0.0077	0.0261	-0.29	0.77
Research	dominator	0.0277	0.0164	1.69	0.09												
	neither / large	0.0072	0.0099	0.72	0.47	-0.0314	0.0260	-1.21	0.23	-0.0073	0.0108	-0.68	0.50	-0.0080	0.0087	-0.91	0.36
	dominated / small	0.0040	0.0114	0.35	0.73	-0.0043	0.0084	-0.51	0.61	-0.0046	0.0098	-0.47	0.64	0.0090	0.0151	0.60	0.55
Patents	dominator	0.0147	0.0192	0.77	0.44												
	neither / large	0.0105	0.0131	0.80	0.42	0.1019	0.0300	3.40	0.00	0.0249	0.0138	1.80	0.07	0.0168	0.0115	1.46	0.14
	dominated / small	0.0121	0.0164	0.74	0.46	0.0042	0.0112	0.37	0.71	-0.0026	0.0133	-0.19	0.85	-0.0113	0.0216	-0.52	0.60
Gini Dominance (D_G)																	
Dominators		0.1925	0.0145	13.27	0.00												
Dominated / Small		-0.1555	0.0109	-14.31	0.00	-0.1242	0.0197	-6.29	0.00	-0.0132	0.0114	-1.17	0.24	0.1331	0.0137	9.73	0.00
Dominance	dominator	0.7243	0.1469	4.93	0.00												
	neither / large	0.2392	0.1054	2.27	0.02	0.8530	0.2443	3.49	0.00	0.2932	0.1118	2.62	0.01	0.1467	0.0910	1.61	0.11
	dominated / small	0.1560	0.1422	1.10	0.27	0.0151	0.0896	0.17	0.87	-0.0721	0.1099	-0.66	0.51	-0.2172	0.1844	-1.18	0.24
Labor	dominator	-0.2319	0.6090	-0.38	0.70												
Pooling	neither / large	1.4011	0.3999	3.50	0.00	-0.6945	0.8279	-0.84	0.40	0.4340	0.4113	1.06	0.29	0.2930	0.3479	0.84	0.40
	dominated / small	0.2460	0.4445	0.55	0.58	0.2858	0.3384	0.84	0.40	-0.1259	0.3925	-0.32	0.75	-0.6997	0.5997	-1.17	0.24
Manufactured	dominator	0.0410	0.0268	1.53	0.13												
Inputs	neither / large	-0.0003	0.0167	-0.02	0.99	0.0253	0.0420	0.60	0.55	-0.0024	0.0178	-0.14	0.89	-0.0040	0.0138	-0.29	0.77
	dominated / small	0.0038	0.0179	0.21	0.83	-0.0076	0.0131	-0.58	0.56	-0.0042	0.0155	-0.27	0.79	-0.0073	0.0249	-0.29	0.77
Producer	dominator	-0.0316	0.0242	-1.31	0.19												
Services	neither / large	0.0310	0.0164	1.90	0.06	-0.0256	0.0381	-0.67	0.50	0.0056	0.0171	0.33	0.74	0.0066	0.0137	0.48	0.63
	dominated / small	-0.0118	0.0185	-0.64	0.52	0.0104	0.0132	0.79	0.43	0.0005	0.0156	0.03	0.98	-0.0121	0.0251	-0.48	0.63
Research	dominator	0.0089	0.0162	0.55	0.59												
	neither / large	-0.0059	0.0097	-0.61	0.54	-0.0288	0.0259	-1.11	0.27	-0.0073	0.0105	-0.69	0.49	-0.0088	0.0085	-1.04	0.30
	dominated / small	-0.0055	0.0113	-0.49	0.63	-0.0072	0.0081	-0.89	0.38	-0.0074	0.0095	-0.78	0.44	0.0055	0.0148	0.38	0.71
Patents	dominator	-0.0216	0.0180	-1.20	0.23												
	neither / large	-0.0125	0.0124	-1.01	0.31	0.0222	0.0272	0.82	0.41	-0.0030	0.0130	-0.23	0.82	0.0017	0.0109	0.16	0.87
	dominated / small	-0.0153	0.0153	-1.00	0.32	-0.0022	0.0107	-0.21	0.84	-0.0004	0.0125	-0.03	0.97	-0.0046	0.0199	-0.23	0.82

Note: "Neither" and "dominated" label the dominance models, "large" and "small" pertain to the small establishment models.

Table A.11.4. Marginal Impacts Including Plant Size Interactions for Metalworking Machinery (SIC 354), 1992.

		Dominance Categories				Small ≤ 250 Employees				Small ≤ 50 Employees				Small ≤ 15 Employees			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
Concentration Ratio Dominance (D_C)																	
Dominators		0.2139	0.0223	9.60	0.00												
Dominated / Small		-0.1984	0.0154	-12.84	0.00	-0.0411	0.0492	-0.84	0.40	-0.0879	0.0193	-4.55	0.00	0.0132	0.0140	0.94	0.35
Dominance	dominator	0.0724	0.0761	0.95	0.34												
	neither / large	-0.1224	0.0484	-2.53	0.01	0.4446	0.2063	2.16	0.03	0.1059	0.0790	1.34	0.18	0.0112	0.0523	0.21	0.83
	dominated / small	-0.1210	0.0663	-1.83	0.07	-0.0174	0.0427	-0.41	0.68	-0.0331	0.0444	-0.75	0.46	-0.0422	0.0518	-0.81	0.42
Labor	dominator	4.7249	2.3084	2.05	0.04												
Pooling	neither / large	-0.4848	1.2325	-0.39	0.69	-0.6734	5.7337	-0.12	0.91	1.5686	1.9355	0.81	0.42	1.8349	1.2188	1.51	0.13
	dominated / small	-0.4572	1.3373	-0.34	0.73	0.7503	1.0059	0.75	0.46	0.4334	1.0497	0.41	0.68	-0.6534	1.2484	-0.52	0.60
Manufactured	dominator	-0.0164	0.0370	-0.44	0.66												
Inputs	neither / large	0.0333	0.0209	1.60	0.11	0.0132	0.0851	0.16	0.88	0.0369	0.0308	1.20	0.23	-0.0078	0.0206	-0.38	0.70
	dominated / small	0.0166	0.0219	0.76	0.45	-0.0141	0.0176	-0.80	0.42	-0.0148	0.0182	-0.81	0.42	-0.0091	0.0211	-0.43	0.67
Producer	dominator	0.0105	0.0247	0.43	0.67												
Services	neither / large	-0.0136	0.0154	-0.88	0.38	0.0160	0.0707	0.23	0.82	-0.0037	0.0227	-0.16	0.87	0.0161	0.0152	1.06	0.29
	dominated / small	-0.0060	0.0156	-0.39	0.70	0.0182	0.0131	1.39	0.17	0.0177	0.0134	1.32	0.19	0.0163	0.0150	1.09	0.28
Research	dominator	-0.0364	0.0193	-1.89	0.06												
	neither / large	-0.0417	0.0114	-3.65	0.00	-0.0872	0.0539	-1.62	0.11	-0.0435	0.0192	-2.26	0.02	-0.0123	0.0122	-1.01	0.31
	dominated / small	-0.0219	0.0128	-1.72	0.09	-0.0070	0.0100	-0.70	0.48	-0.0053	0.0101	-0.53	0.60	-0.0069	0.0112	-0.62	0.54
Patents	dominator	0.0974	0.0335	2.91	0.00												
	neither / large	0.1076	0.0204	5.28	0.00	0.0449	0.0986	0.46	0.65	0.0146	0.0327	0.45	0.66	0.0037	0.0207	0.18	0.86
	dominated / small	0.0378	0.0230	1.64	0.10	-0.0025	0.0167	-0.15	0.88	-0.0052	0.0172	-0.30	0.76	-0.0131	0.0197	-0.66	0.51
Herfindahl-Hirschman Dominance (D_H)																	
Dominators		0.2134	0.0215	9.94	0.00												
Dominated / Small		-0.1939	0.0135	-14.35	0.00	-0.0465	0.0401	-1.16	0.25	-0.0918	0.0175	-5.26	0.00	0.0034	0.0128	0.27	0.79
Dominance	dominator	0.2776	0.1818	1.53	0.13												
	neither / large	-0.2656	0.1203	-2.21	0.03	1.1208	0.5101	2.20	0.03	0.3628	0.2196	1.65	0.10	0.0774	0.1324	0.58	0.56
	dominated / small	-0.1223	0.1931	-0.63	0.53	-0.0690	0.1018	-0.68	0.50	-0.1228	0.1071	-1.15	0.25	-0.1744	0.1334	-1.31	0.19
Labor	dominator	4.5212	2.2692	1.99	0.05												
Pooling	neither / large	0.1291	1.1656	0.11	0.91	-3.8595	5.0309	-0.77	0.44	1.3305	1.7767	0.75	0.45	2.0542	1.1115	1.85	0.06
	dominated / small	0.4264	1.1442	0.37	0.71	0.7870	0.9073	0.87	0.39	0.5631	0.9456	0.60	0.55	-0.7182	1.1234	-0.64	0.52
Manufactured	dominator	-0.0105	0.0367	-0.29	0.77												
Inputs	neither / large	0.0371	0.0202	1.83	0.07	0.0398	0.0825	0.48	0.63	0.0324	0.0301	1.08	0.28	-0.0128	0.0196	-0.66	0.51
	dominated / small	0.0153	0.0201	0.76	0.45	-0.0168	0.0163	-1.03	0.30	-0.0184	0.0169	-1.08	0.28	-0.0097	0.0199	-0.49	0.63
Producer	dominator	0.0021	0.0244	0.09	0.93												
Services	neither / large	-0.0178	0.0149	-1.20	0.23	-0.0187	0.0688	-0.27	0.79	-0.0084	0.0218	-0.39	0.70	0.0147	0.0146	1.00	0.32
	dominated / small	-0.0055	0.0146	-0.37	0.71	0.0150	0.0126	1.19	0.23	0.0153	0.0129	1.19	0.23	0.0120	0.0143	0.84	0.40
Research	dominator	-0.0359	0.0192	-1.86	0.06												
	neither / large	-0.0444	0.0112	-3.95	0.00	-0.0898	0.0537	-1.67	0.09	-0.0428	0.0188	-2.27	0.02	-0.0138	0.0117	-1.18	0.24
	dominated / small	-0.0244	0.0120	-2.04	0.04	-0.0080	0.0093	-0.86	0.39	-0.0056	0.0095	-0.59	0.55	-0.0082	0.0106	-0.77	0.44
Patents	dominator	0.0999	0.0331	3.02	0.00												
	neither / large	0.1107	0.0195	5.67	0.00	0.0486	0.0976	0.50	0.62	0.0242	0.0315	0.77	0.44	0.0108	0.0193	0.56	0.57
	dominated / small	0.0321	0.0211	1.52	0.13	0.0047	0.0150	0.32	0.75	0.0021	0.0156	0.13	0.90	-0.0052	0.0183	-0.28	0.78

Note: "Neither" and "dominated" label the dominance models, "large" and "small" pertain to the small establishment models.

Table A.11.4. Marginal Impacts Including Plant Size Interactions for Metalworking Machinery (SIC 354), 1992, continued.

		Dominance Categories				Small ≤ 250 Employees				Small ≤ 50 Employees				Small ≤ 15 Employees			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
Rosenbluth Dominance (D_R)																	
Dominators		0.2026	0.0220	9.21	0.00												
Dominated / Small		-0.2006	0.0127	-15.78	0.00	-0.0419	0.0385	-1.09	0.28	-0.0885	0.0168	-5.27	0.00	0.0043	0.0123	0.35	0.73
Dominance	dominator	0.2666	0.3443	0.77	0.44												
	neither / large	-0.5433	0.2926	-1.86	0.06	1.9704	1.1418	1.73	0.08	0.6633	0.4669	1.42	0.16	0.3938	0.3320	1.19	0.24
	dominated / small	-0.5522	0.4222	-1.31	0.19	0.1623	0.2733	0.59	0.55	0.1075	0.2826	0.38	0.70	0.0240	0.3162	0.08	0.94
Labor	dominator	4.1744	2.2515	1.85	0.06												
Pooling	neither / large	0.9641	1.1524	0.84	0.40	-3.9318	4.9529	-0.79	0.43	1.1202	1.7285	0.65	0.52	2.3968	1.0900	2.20	0.03
	dominated / small	0.9585	1.1023	0.87	0.38	1.3070	0.8959	1.46	0.14	1.2134	0.9302	1.30	0.19	-0.0272	1.0939	-0.02	0.98
Manufactured	dominator	-0.0064	0.0369	-0.17	0.86												
Inputs	neither / large	0.0291	0.0200	1.46	0.15	0.0578	0.0844	0.69	0.49	0.0472	0.0303	1.56	0.12	-0.0061	0.0197	-0.31	0.76
	dominated / small	0.0133	0.0202	0.66	0.51	-0.0154	0.0164	-0.94	0.35	-0.0177	0.0169	-1.05	0.30	-0.0116	0.0197	-0.59	0.56
Producer	dominator	0.0065	0.0245	0.26	0.79												
Services	neither / large	-0.0096	0.0149	-0.64	0.52	-0.0078	0.0694	-0.11	0.91	-0.0096	0.0217	-0.44	0.66	0.0168	0.0147	1.15	0.25
	dominated / small	-0.0013	0.0146	-0.09	0.93	0.0195	0.0127	1.53	0.12	0.0205	0.0130	1.58	0.11	0.0175	0.0143	1.23	0.22
Research	dominator	-0.0404	0.0198	-2.03	0.04												
	neither / large	-0.0438	0.0113	-3.89	0.00	-0.0988	0.0555	-1.78	0.08	-0.0486	0.0191	-2.55	0.01	-0.0168	0.0117	-1.44	0.15
	dominated / small	-0.0242	0.0119	-2.05	0.04	-0.0094	0.0094	-1.01	0.31	-0.0076	0.0095	-0.80	0.43	-0.0102	0.0107	-0.96	0.34
Patents	dominator	0.0943	0.0352	2.68	0.01												
	neither / large	0.0974	0.0201	4.84	0.00	0.0490	0.1063	0.46	0.64	0.0251	0.0335	0.75	0.45	0.0116	0.0201	0.58	0.56
	dominated / small	0.0272	0.0219	1.24	0.22	0.0044	0.0155	0.28	0.78	0.0010	0.0162	0.06	0.95	-0.0062	0.0192	-0.32	0.75
Gini Dominance (D_G)																	
Dominators		0.1925	0.0209	9.23	0.00												
Dominated / Small		-0.1982	0.0133	-14.92	0.00	-0.0168	0.0481	-0.35	0.73	-0.0939	0.0176	-5.32	0.00	0.0006	0.0129	0.05	0.96
Dominance	dominator	0.4523	0.1602	2.82	0.00												
	neither / large	0.1375	0.0940	1.46	0.14	0.7485	0.6597	1.13	0.26	0.4711	0.1720	2.74	0.01	0.1408	0.1037	1.36	0.17
	dominated / small	0.1260	0.1282	0.98	0.33	0.0020	0.0857	0.02	0.98	-0.0719	0.0893	-0.81	0.42	-0.1281	0.1050	-1.22	0.22
Labor	dominator	4.5950	2.2798	2.02	0.04												
Pooling	neither / large	0.6323	1.2189	0.52	0.60	-3.2085	5.0449	-0.64	0.52	1.8697	1.8122	1.03	0.30	2.4402	1.1631	2.10	0.04
	dominated / small	0.3481	1.1679	0.30	0.77	1.2744	0.9672	1.32	0.19	0.8563	1.0022	0.85	0.39	-0.2788	1.1562	-0.24	0.81
Manufactured	dominator	-0.0271	0.0373	-0.73	0.47												
Inputs	neither / large	0.0235	0.0208	1.13	0.26	0.0103	0.0843	0.12	0.90	0.0164	0.0309	0.53	0.60	-0.0223	0.0198	-1.13	0.26
	dominated / small	0.0054	0.0203	0.27	0.79	-0.0207	0.0162	-1.28	0.20	-0.0212	0.0169	-1.26	0.21	-0.0109	0.0199	-0.55	0.58
Producer	dominator	-0.0024	0.0241	-0.10	0.92												
Services	neither / large	-0.0151	0.0148	-1.02	0.31	-0.0255	0.0681	-0.37	0.71	-0.0098	0.0220	-0.45	0.66	0.0195	0.0149	1.31	0.19
	dominated / small	0.0006	0.0149	0.04	0.97	0.0196	0.0128	1.53	0.13	0.0191	0.0131	1.46	0.14	0.0160	0.0144	1.11	0.27
Research	dominator	-0.0228	0.0194	-1.17	0.24												
	neither / large	-0.0381	0.0114	-3.36	0.00	-0.0801	0.0554	-1.44	0.15	-0.0370	0.0189	-1.95	0.05	-0.0170	0.0117	-1.45	0.15
	dominated / small	-0.0217	0.0122	-1.79	0.07	-0.0126	0.0093	-1.36	0.17	-0.0110	0.0095	-1.16	0.25	-0.0149	0.0106	-1.40	0.16
Patents	dominator	0.0654	0.0338	1.93	0.05												
	neither / large	0.1165	0.0207	5.62	0.00	-0.0438	0.0932	-0.47	0.64	-0.0291	0.0324	-0.90	0.37	0.0016	0.0197	0.08	0.93
	dominated / small	0.0177	0.0220	0.80	0.42	0.0108	0.0155	0.70	0.48	0.0143	0.0161	0.89	0.37	0.0155	0.0186	0.83	0.41

Note: "Neither" and "dominated" label the dominance models, "large" and "small" pertain to the small establishment models.

Table A.11.5. Marginal Impacts Including Plant Size Interactions for Metalworking Machinery (SIC 354), 1997.

		Dominance Categories				Small ≤ 250 Employees				Small ≤ 50 Employees				Small ≤ 15 Employees			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
Concentration Ratio Dominance (D_C)																	
Dominators		0.2254	0.0199	11.30	0.00												
Dominated / Small		-0.1470	0.0142	-10.38	0.00	-0.1750	0.0470	-3.72	0.00	-0.0351	0.0172	-2.04	0.04	0.0306	0.0132	2.32	0.02
Dominance	dominator	0.0244	0.0764	0.32	0.75												
	neither / large	-0.1649	0.0487	-3.39	0.00	-0.1251	0.1763	-0.71	0.48	0.0840	0.0682	1.23	0.22	-0.0400	0.0479	-0.83	0.40
	dominated / small	-0.3104	0.0585	-5.30	0.00	-0.1101	0.0416	-2.65	0.01	-0.1383	0.0434	-3.19	0.00	-0.1804	0.0501	-3.60	0.00
Labor	dominator	-3.6442	1.7737	-2.05	0.04												
Pooling	neither / large	-2.2124	1.0843	-2.04	0.04	-11.0570	4.5390	-2.44	0.01	-1.8475	1.5569	-1.19	0.24	-1.4533	1.0792	-1.35	0.18
	dominated / small	-3.5986	1.1913	-3.02	0.00	-1.8869	0.9587	-1.97	0.05	-1.8421	0.9950	-1.85	0.06	-2.7240	1.1534	-2.36	0.02
Manufactured	dominator	0.0750	0.0422	1.78	0.08												
Inputs	neither / large	0.0154	0.0224	0.68	0.49	0.2356	0.1156	2.04	0.04	0.0090	0.0356	0.25	0.80	-0.0010	0.0222	-0.05	0.96
	dominated / small	0.0346	0.0242	1.43	0.15	0.0033	0.0181	0.18	0.85	0.0079	0.0191	0.42	0.68	0.0211	0.0231	0.91	0.36
Producer	dominator	-0.0590	0.0333	-1.77	0.08												
Services	neither / large	-0.0254	0.0193	-1.32	0.19	-0.2409	0.0895	-2.69	0.01	-0.0224	0.0295	-0.76	0.45	-0.0078	0.0192	-0.41	0.68
	dominated / small	-0.0637	0.0211	-3.01	0.00	-0.0166	0.0162	-1.02	0.31	-0.0168	0.0169	-1.00	0.32	-0.0339	0.0201	-1.69	0.09
Research	dominator	-0.0131	0.0200	-0.66	0.51												
	neither / large	0.0017	0.0127	0.13	0.89	-0.0072	0.0491	-0.15	0.88	-0.0093	0.0184	-0.51	0.61	0.0027	0.0127	0.21	0.83
	dominated / small	0.0108	0.0130	0.83	0.41	0.0047	0.0109	0.43	0.67	0.0040	0.0112	0.36	0.72	0.0042	0.0123	0.35	0.73
Patents	dominator	0.0959	0.0288	3.33	0.00												
	neither / large	0.1032	0.0179	5.77	0.00	-0.0592	0.0842	-0.70	0.48	0.0457	0.0261	1.75	0.08	0.0378	0.0174	2.18	0.03
	dominated / small	0.0671	0.0192	3.49	0.00	0.0257	0.0145	1.78	0.08	0.0202	0.0152	1.34	0.18	0.0107	0.0176	0.61	0.54
Herfindahl-Hirschman Dominance (D_H)																	
Dominators		0.2217	0.0177	12.52	0.00												
Dominated / Small		-0.1348	0.0118	-11.47	0.00	-0.1272	0.0358	-3.55	0.00	-0.0303	0.0149	-2.03	0.04	0.0260	0.0116	2.24	0.03
Dominance	dominator	0.1957	0.1548	1.26	0.21												
	neither / large	-0.1491	0.1032	-1.45	0.15	-0.1969	0.3965	-0.50	0.62	0.2756	0.1552	1.78	0.08	0.0207	0.0997	0.21	0.84
	dominated / small	-0.4435	0.1291	-3.44	0.00	-0.1212	0.0790	-1.53	0.12	-0.1915	0.0838	-2.28	0.02	-0.2662	0.1032	-2.58	0.01
Labor	dominator	-2.8230	1.6876	-1.67	0.09												
Pooling	neither / large	-0.9240	1.0273	-0.90	0.37	-12.3913	3.8904	-3.19	0.00	-1.5370	1.4226	-1.08	0.28	-0.3385	0.9717	-0.35	0.73
	dominated / small	-1.6515	1.0525	-1.57	0.12	-0.4790	0.8597	-0.56	0.58	-0.3662	0.8939	-0.41	0.68	-1.0781	1.0412	-1.04	0.30
Manufactured	dominator	0.0714	0.0413	1.73	0.08												
Inputs	neither / large	0.0094	0.0221	0.42	0.67	0.3053	0.1098	2.78	0.01	0.0118	0.0351	0.34	0.74	-0.0066	0.0214	-0.31	0.76
	dominated / small	0.0285	0.0230	1.24	0.21	-0.0044	0.0171	-0.26	0.80	-0.0006	0.0181	-0.04	0.97	0.0118	0.0220	0.54	0.59
Producer	dominator	-0.0569	0.0321	-1.77	0.08												
Services	neither / large	-0.0141	0.0187	-0.76	0.45	-0.2726	0.0817	-3.33	0.00	-0.0244	0.0279	-0.87	0.38	0.0032	0.0181	0.18	0.86
	dominated / small	-0.0402	0.0195	-2.06	0.04	-0.0009	0.0152	-0.06	0.95	0.0004	0.0159	0.02	0.98	-0.0139	0.0187	-0.74	0.46
Research	dominator	-0.0166	0.0198	-0.84	0.40												
	neither / large	-0.0042	0.0124	-0.34	0.74	-0.0147	0.0490	-0.30	0.76	-0.0130	0.0179	-0.73	0.47	-0.0044	0.0118	-0.37	0.71
	dominated / small	-0.0028	0.0116	-0.24	0.81	-0.0032	0.0098	-0.33	0.74	-0.0031	0.0101	-0.30	0.76	-0.0033	0.0113	-0.29	0.77
Patents	dominator	0.0979	0.0277	3.53	0.00												
	neither / large	0.1123	0.0173	6.49	0.00	-0.0205	0.0849	-0.24	0.81	0.0480	0.0250	1.92	0.05	0.0421	0.0162	2.60	0.01
	dominated / small	0.0767	0.0177	4.33	0.00	0.0324	0.0133	2.44	0.01	0.0296	0.0140	2.12	0.03	0.0243	0.0164	1.47	0.14

Note: "Neither" and "dominated" label the dominance models, "large" and "small" pertain to the small establishment models.

Table A.11.5. Marginal Impacts Including Plant Size Interactions for Metalworking Machinery (SIC 354), 1997, continued.

		Dominance Categories				Small ≤ 250 Employees				Small ≤ 50 Employees				Small ≤ 15 Employees			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
Rosenbluth Dominance (D_R)																	
Dominators		0.2172	0.0179	12.14	0.00												
Dominated / Small		-0.1362	0.0119	-11.46	0.00	-0.1374	0.0347	-3.96	0.00	-0.0254	0.0148	-1.72	0.09	0.0255	0.0115	2.22	0.03
Dominance	dominator	-0.3494	0.2641	-1.32	0.19												
	neither / large	-0.6428	0.2166	-2.97	0.00	-0.5697	0.6785	-0.84	0.40	-0.0489	0.3246	-0.15	0.88	0.1434	0.2269	0.63	0.53
	dominated / small	-1.0087	0.3777	-2.67	0.01	-0.1885	0.1915	-0.98	0.33	-0.2064	0.1992	-1.04	0.30	-0.5522	0.2298	-2.40	0.02
Labor	dominator	-2.5182	1.6881	-1.49	0.14												
Pooling	neither / large	-0.4776	1.0317	-0.46	0.64	-11.1809	3.8187	-2.93	0.00	-1.8250	1.4032	-1.30	0.19	-0.1140	0.9745	-0.12	0.91
	dominated / small	-0.6766	1.0190	-0.66	0.51	-0.1160	0.8633	-0.13	0.89	0.1466	0.8946	0.16	0.87	-0.5844	1.0288	-0.57	0.57
Manufactured	dominator	0.0639	0.0417	1.53	0.13												
Inputs	neither / large	0.0026	0.0219	0.12	0.91	0.2571	0.1084	2.37	0.02	0.0206	0.0348	0.59	0.55	-0.0040	0.0214	-0.19	0.85
	dominated / small	0.0088	0.0227	0.39	0.70	-0.0114	0.0170	-0.67	0.50	-0.0109	0.0180	-0.61	0.54	-0.0049	0.0217	-0.23	0.82
Producer	dominator	-0.0536	0.0320	-1.67	0.09												
Services	neither / large	-0.0096	0.0186	-0.52	0.60	-0.2464	0.0793	-3.11	0.00	-0.0294	0.0274	-1.07	0.28	0.0061	0.0179	0.34	0.73
	dominated / small	-0.0238	0.0188	-1.27	0.21	0.0057	0.0151	0.38	0.70	0.0100	0.0157	0.64	0.52	-0.0040	0.0183	-0.22	0.83
Research	dominator	-0.0181	0.0201	-0.90	0.37												
	neither / large	-0.0081	0.0123	-0.66	0.51	-0.0068	0.0495	-0.14	0.89	-0.0164	0.0179	-0.91	0.36	-0.0085	0.0117	-0.73	0.47
	dominated / small	-0.0081	0.0116	-0.70	0.48	-0.0059	0.0097	-0.61	0.54	-0.0058	0.0100	-0.57	0.57	-0.0046	0.0113	-0.41	0.68
Patents	dominator	0.0768	0.0281	2.73	0.01												
	neither / large	0.0978	0.0176	5.56	0.00	-0.0376	0.0797	-0.47	0.64	0.0299	0.0256	1.17	0.24	0.0432	0.0168	2.58	0.01
	dominated / small	0.0667	0.0187	3.57	0.00	0.0313	0.0139	2.25	0.02	0.0312	0.0146	2.14	0.03	0.0177	0.0171	1.03	0.30
Gini Dominance (D_G)																	
Dominators		0.2371	0.0191	12.40	0.00												
Dominated / Small		-0.1361	0.0128	-10.67	0.00	-0.1432	0.0419	-3.42	0.00	-0.0326	0.0159	-2.06	0.04	0.0257	0.0122	2.11	0.04
Dominance	dominator	0.6917	0.1458	4.74	0.00												
	neither / large	0.1364	0.0902	1.51	0.13	-0.1503	0.5432	-0.28	0.78	0.4827	0.1500	3.22	0.00	0.0275	0.0933	0.29	0.77
	dominated / small	-0.0320	0.1119	-0.29	0.78	-0.0546	0.0760	-0.72	0.47	-0.1272	0.0791	-1.61	0.11	-0.1202	0.0933	-1.29	0.20
Labor	dominator	-2.2299	1.6689	-1.34	0.18												
Pooling	neither / large	-0.2620	1.0450	-0.25	0.80	-11.0142	4.1391	-2.66	0.01	-0.6185	1.4448	-0.43	0.67	-0.2360	0.9939	-0.24	0.81
	dominated / small	-0.5874	1.0865	-0.54	0.59	-0.3608	0.8933	-0.40	0.69	-0.1746	0.9231	-0.19	0.85	-0.6767	1.0665	-0.63	0.53
Manufactured	dominator	0.0632	0.0406	1.56	0.12												
Inputs	neither / large	0.0026	0.0221	0.12	0.90	0.2576	0.1108	2.33	0.02	-0.0194	0.0355	-0.55	0.58	-0.0127	0.0217	-0.59	0.56
	dominated / small	0.0073	0.0233	0.31	0.75	-0.0081	0.0175	-0.46	0.64	-0.0026	0.0183	-0.14	0.89	0.0055	0.0221	0.25	0.81
Producer	dominator	-0.0571	0.0318	-1.80	0.07												
Services	neither / large	-0.0022	0.0188	-0.12	0.91	-0.2437	0.0836	-2.91	0.00	-0.0096	0.0279	-0.35	0.73	0.0060	0.0184	0.32	0.75
	dominated / small	-0.0146	0.0198	-0.74	0.46	0.0025	0.0156	0.16	0.87	0.0046	0.0162	0.28	0.78	-0.0049	0.0190	-0.26	0.79
Research	dominator	-0.0167	0.0198	-0.85	0.40												
	neither / large	-0.0115	0.0124	-0.93	0.35	-0.0152	0.0496	-0.31	0.76	-0.0043	0.0179	-0.24	0.81	-0.0060	0.0117	-0.52	0.61
	dominated / small	-0.0089	0.0117	-0.76	0.45	-0.0047	0.0097	-0.49	0.62	-0.0066	0.0100	-0.66	0.51	-0.0065	0.0113	-0.58	0.56
Patents	dominator	0.0643	0.0271	2.37	0.02												
	neither / large	0.1078	0.0172	6.27	0.00	-0.0307	0.0747	-0.41	0.68	0.0154	0.0241	0.64	0.52	0.0357	0.0163	2.19	0.03
	dominated / small	0.0704	0.0185	3.81	0.00	0.0386	0.0139	2.78	0.01	0.0413	0.0145	2.85	0.00	0.0381	0.0169	2.26	0.02

Note: "Neither" and "dominated" label the dominance models, "large" and "small" pertain to the small establishment models.

Table A.11.6. Marginal Impacts Including Plant Size Interactions for Metalworking Machinery (SIC 354), 2002.

		Dominance Categories				Small ≤ 250 Employees				Small ≤ 50 Employees				Small ≤ 15 Employees			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
Concentration Ratio Dominance (D_C)																	
Dominators		0.1785	0.0238	7.49	0.00												
Dominated / Small		-0.1649	0.0197	-8.37	0.00	-0.0865	0.0613	-1.41	0.16	-0.0627	0.0228	-2.75	0.01	0.0505	0.0173	2.91	0.00
Dominance	dominator	-0.1127	0.0839	-1.34	0.18												
	neither / large	-0.2016	0.0605	-3.34	0.00	0.1612	0.2153	0.75	0.45	-0.0621	0.0990	-0.63	0.53	-0.0340	0.0641	-0.53	0.60
	dominated / small	-0.1906	0.1039	-1.84	0.07	-0.0752	0.0532	-1.41	0.16	-0.0726	0.0552	-1.32	0.19	-0.1145	0.0660	-1.73	0.08
Labor	dominator	1.7215	1.1977	1.44	0.15												
Pooling	neither / large	0.1833	0.7385	0.25	0.80	-2.4017	4.4641	-0.54	0.59	-0.3869	1.1214	-0.35	0.73	0.9169	0.7586	1.21	0.23
	dominated / small	-0.4248	0.9386	-0.45	0.65	0.0918	0.6503	0.14	0.89	0.2242	0.6781	0.33	0.74	-0.7844	0.8104	-0.97	0.33
Manufactured	dominator	-0.0807	0.0417	-1.93	0.05												
Inputs	neither / large	-0.0474	0.0232	-2.05	0.04	-0.1448	0.1389	-1.04	0.30	0.0105	0.0382	0.28	0.78	-0.0524	0.0229	-2.29	0.02
	dominated / small	-0.0278	0.0272	-1.02	0.31	-0.0433	0.0187	-2.32	0.02	-0.0501	0.0196	-2.56	0.01	-0.0382	0.0249	-1.54	0.12
Producer	dominator	0.1027	0.0348	2.95	0.00												
Services	neither / large	0.0385	0.0208	1.85	0.06	0.0703	0.1347	0.52	0.60	0.0130	0.0322	0.41	0.68	0.0448	0.0205	2.19	0.03
	dominated / small	0.0015	0.0234	0.07	0.95	0.0215	0.0176	1.23	0.22	0.0238	0.0182	1.31	0.19	0.0014	0.0221	0.06	0.95
Research	dominator	-0.0293	0.0214	-1.37	0.17												
	neither / large	-0.0263	0.0136	-1.94	0.05	0.0890	0.0657	1.35	0.18	-0.0297	0.0218	-1.37	0.17	-0.0148	0.0139	-1.06	0.29
	dominated / small	-0.0121	0.0158	-0.76	0.45	-0.0048	0.0114	-0.42	0.67	-0.0007	0.0117	-0.06	0.95	0.0086	0.0137	0.63	0.53
Patents	dominator	0.1279	0.0308	4.16	0.00												
	neither / large	0.1027	0.0208	4.93	0.00	0.0726	0.1082	0.67	0.50	0.0677	0.0324	2.09	0.04	0.0579	0.0210	2.76	0.01
	dominated / small	0.1107	0.0260	4.25	0.00	0.0361	0.0173	2.08	0.04	0.0305	0.0180	1.70	0.09	0.0150	0.0213	0.70	0.48
Herfindahl-Hirschman Dominance (D_H)																	
Dominators		0.2133	0.0207	10.31	0.00												
Dominated / Small		-0.1656	0.0150	-11.06	0.00	-0.1705	0.0495	-3.44	0.00	-0.1138	0.0187	-6.07	0.00	0.0321	0.0148	2.17	0.03
Dominance	dominator	0.0294	0.1650	0.18	0.86												
	neither / large	-0.1092	0.1257	-0.87	0.39	0.6063	0.3963	1.53	0.13	0.5670	0.2121	2.67	0.01	0.2119	0.1334	1.59	0.11
	dominated / small	-0.1529	0.2104	-0.73	0.47	0.0453	0.1082	0.42	0.68	-0.0315	0.1123	-0.28	0.78	-0.1052	0.1391	-0.76	0.45
Labor	dominator	2.1953	1.1966	1.83	0.07												
Pooling	neither / large	0.2152	0.7134	0.30	0.76	1.5045	4.1662	0.36	0.72	0.3046	1.0402	0.29	0.77	0.9159	0.7064	1.30	0.19
	dominated / small	-0.7294	0.8419	-0.87	0.39	-0.0008	0.6077	0.00	1.00	0.0254	0.6395	0.04	0.97	-0.9799	0.7723	-1.27	0.20
Manufactured	dominator	-0.0729	0.0422	-1.73	0.08												
Inputs	neither / large	-0.0462	0.0232	-1.99	0.05	-0.1837	0.1397	-1.31	0.19	0.0138	0.0384	0.36	0.72	-0.0536	0.0230	-2.33	0.02
	dominated / small	-0.0322	0.0275	-1.17	0.24	-0.0410	0.0189	-2.16	0.03	-0.0488	0.0198	-2.46	0.01	-0.0354	0.0252	-1.40	0.16
Producer	dominator	0.0977	0.0350	2.79	0.01												
Services	neither / large	0.0354	0.0206	1.72	0.09	0.1387	0.1324	1.05	0.30	0.0169	0.0319	0.53	0.60	0.0460	0.0201	2.29	0.02
	dominated / small	0.0021	0.0231	0.09	0.93	0.0214	0.0172	1.24	0.21	0.0230	0.0179	1.28	0.20	0.0015	0.0220	0.07	0.94
Research	dominator	-0.0354	0.0213	-1.66	0.10												
	neither / large	-0.0316	0.0133	-2.37	0.02	0.0805	0.0671	1.20	0.23	-0.0412	0.0214	-1.93	0.05	-0.0201	0.0134	-1.50	0.13
	dominated / small	-0.0158	0.0150	-1.05	0.29	-0.0083	0.0108	-0.77	0.44	-0.0040	0.0112	-0.36	0.72	0.0059	0.0132	0.45	0.65
Patents	dominator	0.1301	0.0302	4.31	0.00												
	neither / large	0.0982	0.0201	4.87	0.00	0.1309	0.1138	1.15	0.25	0.0687	0.0311	2.21	0.03	0.0537	0.0199	2.69	0.01
	dominated / small	0.0994	0.0248	4.01	0.00	0.0329	0.0163	2.01	0.04	0.0248	0.0170	1.46	0.15	0.0157	0.0204	0.77	0.44

Note: "Neither" and "dominated" label the dominance models, "large" and "small" pertain to the small establishment models.

Table A.11.6. Marginal Impacts Including Plant Size Interactions for Metalworking Machinery (SIC 354), 2002, continued.

		Dominance Categories				Small ≤ 250 Employees				Small ≤ 50 Employees				Small ≤ 15 Employees			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
Rosenbluth Dominance (D_R)																	
Dominators		0.2048	0.0211	9.71	0.00												
Dominated / Small		-0.1637	0.0149	-11.01	0.00	-0.1896	0.0468	-4.05	0.00	-0.1117	0.0185	-6.04	0.00	0.0330	0.0146	2.26	0.02
Dominance	dominator	-0.1380	0.2460	-0.56	0.57												
	neither / large	-0.1965	0.2238	-0.88	0.38	1.2213	0.6504	1.88	0.06	0.8642	0.3279	2.64	0.01	0.3863	0.2290	1.69	0.09
	dominated / small	-0.7526	0.3765	-2.00	0.05	0.0598	0.2010	0.30	0.77	-0.0703	0.2077	-0.34	0.73	-0.2340	0.2490	-0.94	0.35
Labor	dominator	2.1883	1.1889	1.84	0.07												
Pooling	neither / large	0.2740	0.7189	0.38	0.70	1.1499	4.1736	0.28	0.78	0.1593	1.0449	0.15	0.88	0.8967	0.7206	1.24	0.21
	dominated / small	-0.5989	0.8526	-0.70	0.48	0.0756	0.6249	0.12	0.90	0.1475	0.6559	0.22	0.82	-0.8292	0.7844	-1.06	0.29
Manufactured	dominator	-0.0712	0.0423	-1.68	0.09												
Inputs	neither / large	-0.0441	0.0232	-1.90	0.06	-0.1600	0.1398	-1.14	0.25	0.0216	0.0386	0.56	0.58	-0.0461	0.0231	-2.00	0.05
	dominated / small	-0.0389	0.0276	-1.41	0.16	-0.0377	0.0189	-2.00	0.05	-0.0464	0.0198	-2.34	0.02	-0.0349	0.0253	-1.38	0.17
Producer	dominator	0.0954	0.0348	2.74	0.01												
Services	neither / large	0.0344	0.0206	1.67	0.10	0.1479	0.1319	1.12	0.26	0.0183	0.0319	0.58	0.57	0.0455	0.0202	2.25	0.02
	dominated / small	0.0043	0.0232	0.19	0.85	0.0220	0.0174	1.26	0.21	0.0235	0.0181	1.30	0.19	0.0014	0.0221	0.06	0.95
Research	dominator	-0.0367	0.0214	-1.72	0.09												
	neither / large	-0.0291	0.0135	-2.16	0.03	0.0840	0.0667	1.26	0.21	-0.0414	0.0215	-1.93	0.05	-0.0204	0.0136	-1.50	0.13
	dominated / small	-0.0145	0.0152	-0.95	0.34	-0.0093	0.0110	-0.84	0.40	-0.0049	0.0114	-0.43	0.67	0.0053	0.0134	0.39	0.69
Patents	dominator	0.1274	0.0311	4.10	0.00												
	neither / large	0.0990	0.0208	4.76	0.00	0.1152	0.1111	1.04	0.30	0.0758	0.0322	2.35	0.02	0.0596	0.0207	2.88	0.00
	dominated / small	0.0868	0.0257	3.38	0.00	0.0334	0.0170	1.97	0.05	0.0232	0.0177	1.31	0.19	0.0097	0.0213	0.46	0.65
Gini Dominance (D_G)																	
Dominators		0.2352	0.0223	10.55	0.00												
Dominated / Small		-0.1800	0.0166	-10.87	0.00	-0.1243	0.0660	-1.88	0.06	-0.1052	0.0199	-5.29	0.00	0.0290	0.0156	1.86	0.06
Dominance	dominator	0.7003	0.1612	4.34	0.00												
	neither / large	0.2037	0.1137	1.79	0.07	1.9177	0.7542	2.54	0.01	0.9129	0.2016	4.53	0.00	0.2291	0.1195	1.92	0.06
	dominated / small	0.3164	0.1615	1.96	0.05	0.0664	0.0966	0.69	0.49	-0.0171	0.1008	-0.17	0.87	-0.0066	0.1234	-0.05	0.96
Labor	dominator	2.6541	1.1881	2.23	0.03												
Pooling	neither / large	0.7146	0.7260	0.98	0.33	2.1393	4.2975	0.50	0.62	1.1607	1.0808	1.07	0.28	1.0239	0.7276	1.41	0.16
	dominated / small	-0.5881	0.9139	-0.64	0.52	-0.1240	0.6306	-0.20	0.84	-0.0265	0.6625	-0.04	0.97	-1.0928	0.7932	-1.38	0.17
Manufactured	dominator	-0.0742	0.0412	-1.80	0.07												
Inputs	neither / large	-0.0438	0.0233	-1.88	0.06	-0.1551	0.1385	-1.12	0.26	-0.0107	0.0382	-0.28	0.78	-0.0533	0.0237	-2.25	0.02
	dominated / small	-0.0304	0.0281	-1.08	0.28	-0.0302	0.0195	-1.55	0.12	-0.0344	0.0204	-1.69	0.09	-0.0114	0.0254	-0.45	0.65
Producer	dominator	0.0825	0.0343	2.41	0.02												
Services	neither / large	0.0322	0.0204	1.58	0.11	0.1192	0.1341	0.89	0.37	0.0209	0.0320	0.65	0.51	0.0434	0.0204	2.13	0.03
	dominated / small	-0.0026	0.0238	-0.11	0.91	0.0167	0.0176	0.95	0.34	0.0194	0.0183	1.06	0.29	-0.0054	0.0223	-0.24	0.81
Research	dominator	-0.0201	0.0215	-0.94	0.35												
	neither / large	-0.0314	0.0140	-2.24	0.03	0.0687	0.0652	1.05	0.29	-0.0287	0.0216	-1.33	0.18	-0.0178	0.0137	-1.30	0.19
	dominated / small	-0.0181	0.0152	-1.19	0.23	-0.0098	0.0111	-0.88	0.38	-0.0069	0.0115	-0.60	0.55	0.0017	0.0136	0.13	0.90
Patents	dominator	0.1025	0.0290	3.53	0.00												
	neither / large	0.0698	0.0200	3.49	0.00	-0.0026	0.1029	-0.03	0.98	0.0001	0.0301	0.00	1.00	0.0243	0.0198	1.22	0.22
	dominated / small	0.0535	0.0263	2.04	0.04	0.0185	0.0162	1.14	0.25	0.0176	0.0170	1.04	0.30	0.0100	0.0199	0.50	0.61

Note: "Neither" and "dominated" label the dominance models, "large" and "small" pertain to the small establishment models.

Table A.11.7. Marginal Impacts Including Plant Size Interactions for Measuring and Controlling Devices (SIC 382), 1992.

		Dominance Categories				Small ≤ 250 Employees				Small ≤ 50 Employees				Small ≤ 15 Employees			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
Concentration Ratio Dominance (D_C)																	
Dominators		0.2256	0.0514	4.39	0.00												
Dominated / Small		-0.3221	0.0393	-8.19	0.00	-0.0535	0.0580	-0.92	0.36	-0.1577	0.0403	-3.91	0.00	-0.0860	0.0437	-1.97	0.05
Dominance	dominator	-0.4002	0.2614	-1.53	0.13												
	neither / large	-0.3731	0.2149	-1.74	0.08	-0.2907	0.3164	-0.92	0.36	-0.1736	0.2315	-0.75	0.45	-0.1940	0.2236	-0.87	0.39
	dominated / small	-0.5132	0.2333	-2.20	0.03	-0.1695	0.1931	-0.88	0.38	-0.2934	0.2119	-1.38	0.17	-0.4761	0.2549	-1.87	0.06
Labor	dominator	0.5425	2.1364	0.25	0.80												
Pooling	neither / large	0.8845	1.1551	0.77	0.44	6.1252	2.9753	2.06	0.04	1.2334	1.3056	0.94	0.34	0.7206	1.0801	0.67	0.50
	dominated / small	0.5153	1.2268	0.42	0.67	2.0907	0.8883	2.35	0.02	1.2975	1.0662	1.22	0.22	3.4284	1.5833	2.17	0.03
Manufactured	dominator	-0.0249	0.0609	-0.41	0.68												
Inputs	neither / large	0.0361	0.0354	1.02	0.31	-0.1948	0.0865	-2.25	0.02	-0.0388	0.0423	-0.92	0.36	-0.0408	0.0346	-1.18	0.24
	dominated / small	0.0216	0.0401	0.54	0.59	-0.0395	0.0281	-1.40	0.16	-0.0414	0.0330	-1.25	0.21	-0.0563	0.0475	-1.19	0.24
Producer	dominator	0.0007	0.0472	0.01	0.99												
Services	neither / large	-0.0133	0.0299	-0.45	0.66	0.1189	0.0657	1.81	0.07	0.0266	0.0343	0.78	0.44	0.0288	0.0290	1.00	0.32
	dominated / small	-0.0107	0.0339	-0.32	0.75	0.0200	0.0241	0.83	0.41	0.0303	0.0284	1.07	0.29	0.0178	0.0413	0.43	0.67
Research	dominator	0.0157	0.0302	0.52	0.60												
	neither / large	0.0063	0.0166	0.38	0.70	0.0371	0.0359	1.03	0.30	0.0193	0.0199	0.97	0.33	0.0262	0.0155	1.68	0.09
	dominated / small	0.0089	0.0175	0.51	0.61	0.0220	0.0126	1.75	0.08	0.0136	0.0147	0.92	0.36	0.0071	0.0223	0.32	0.75
Patents	dominator	0.0689	0.1032	0.67	0.50												
	neither / large	0.0724	0.0643	1.13	0.26	0.1171	0.1124	1.04	0.30	0.1015	0.0641	1.58	0.11	0.0409	0.0547	0.75	0.45
	dominated / small	0.0188	0.0617	0.30	0.76	0.0308	0.0474	0.65	0.52	0.0081	0.0579	0.14	0.89	-0.1274	0.0890	-1.43	0.15
Herfindahl-Hirschman Dominance (D_H)																	
Dominators		0.2646	0.0486	5.45	0.00												
Dominated / Small		-0.3158	0.0330	-9.56	0.00	-0.0644	0.0557	-1.16	0.25	-0.1785	0.0364	-4.91	0.00	-0.1239	0.0390	-3.18	0.00
Dominance	dominator	-0.2800	0.3792	-0.74	0.46												
	neither / large	-0.4016	0.3266	-1.23	0.22	-0.6178	0.6363	-0.97	0.33	-0.2585	0.3983	-0.65	0.52	-0.3046	0.3861	-0.79	0.43
	dominated / small	-0.5746	0.4551	-1.26	0.21	-0.2955	0.3190	-0.93	0.35	-0.5616	0.3536	-1.59	0.11	-0.9030	0.4127	-2.19	0.03
Labor	dominator	0.9869	2.1288	0.46	0.64												
Pooling	neither / large	1.0036	1.1420	0.88	0.38	6.3945	2.9509	2.17	0.03	1.1654	1.2739	0.91	0.36	0.6785	1.0327	0.66	0.51
	dominated / small	-0.0616	1.1870	-0.05	0.96	2.0320	0.8466	2.40	0.02	1.5038	1.0289	1.46	0.14	3.6224	1.5815	2.29	0.02
Manufactured	dominator	-0.0688	0.0660	-1.04	0.30												
Inputs	neither / large	-0.0074	0.0365	-0.20	0.84	-0.2158	0.0875	-2.47	0.01	-0.0404	0.0425	-0.95	0.34	-0.0480	0.0340	-1.41	0.16
	dominated / small	0.0270	0.0392	0.69	0.49	-0.0479	0.0279	-1.72	0.09	-0.0575	0.0329	-1.75	0.08	-0.0721	0.0492	-1.46	0.14
Producer	dominator	0.0208	0.0472	0.44	0.66												
Services	neither / large	0.0139	0.0295	0.47	0.64	0.1112	0.0649	1.71	0.09	0.0216	0.0336	0.64	0.52	0.0279	0.0281	0.99	0.32
	dominated / small	-0.0089	0.0329	-0.27	0.79	0.0201	0.0233	0.86	0.39	0.0334	0.0276	1.21	0.23	0.0200	0.0409	0.49	0.62
Research	dominator	0.0321	0.0300	1.07	0.29												
	neither / large	0.0112	0.0163	0.69	0.49	0.0489	0.0353	1.38	0.17	0.0229	0.0192	1.19	0.24	0.0284	0.0149	1.90	0.06
	dominated / small	0.0112	0.0166	0.67	0.50	0.0235	0.0120	1.97	0.05	0.0199	0.0140	1.42	0.16	0.0087	0.0216	0.40	0.69
Patents	dominator	0.1411	0.1103	1.28	0.20												
	neither / large	0.1444	0.0695	2.08	0.04	0.1391	0.1145	1.21	0.22	0.1147	0.0678	1.69	0.09	0.0711	0.0580	1.23	0.22
	dominated / small	0.0786	0.0625	1.26	0.21	0.0455	0.0508	0.90	0.37	0.0355	0.0604	0.59	0.56	-0.1061	0.0925	-1.15	0.25

Note: "Neither" and "dominated" label the dominance models, "large" and "small" pertain to the small establishment models.

Table A.11.7. Marginal Impacts Including Plant Size Interactions for Measuring and Controlling Devices (SIC 382), 1992, continued.

		Dominance Categories				Small ≤ 250 Employees				Small ≤ 50 Employees				Small ≤ 15 Employees			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
Rosenbluth Dominance (D_R)																	
Dominators		0.2749	0.0509	5.40	0.00												
Dominated / Small		-0.3105	0.0329	-9.43	0.00	-0.0505	0.0548	-0.92	0.36	-0.1614	0.0362	-4.46	0.00	-0.0464	0.0354	-1.31	0.19
Dominance	dominator	-1.6258	0.7994	-2.03	0.04												
	neither / large	-1.9202	0.7285	-2.64	0.01	-1.9777	1.3802	-1.43	0.15	-1.3522	0.8848	-1.53	0.13	-0.9661	0.7540	-1.28	0.20
	dominated / small	-2.1572	1.0268	-2.10	0.04	-0.8999	0.7003	-1.29	0.20	-1.6709	0.7894	-2.12	0.03	-1.4889	0.8194	-1.82	0.07
Labor	dominator	-0.2130	2.1685	-0.10	0.92												
Pooling	neither / large	0.2014	1.1370	0.18	0.86	6.1776	2.9406	2.10	0.04	1.2136	1.2769	0.95	0.34	1.1947	0.9277	1.29	0.20
	dominated / small	0.0528	1.1708	0.05	0.96	2.1487	0.8380	2.56	0.01	1.4391	1.0208	1.41	0.16	3.5400	1.4092	2.51	0.01
Manufactured	dominator	-0.0090	0.0637	-0.14	0.89												
Inputs	neither / large	0.0376	0.0356	1.06	0.29	-0.2007	0.0864	-2.32	0.02	-0.0353	0.0421	-0.84	0.40	-0.0452	0.0301	-1.50	0.13
	dominated / small	0.0189	0.0388	0.49	0.63	-0.0419	0.0272	-1.54	0.12	-0.0486	0.0324	-1.50	0.13	-0.0553	0.0429	-1.29	0.20
Producer	dominator	-0.0108	0.0474	-0.23	0.82												
Services	neither / large	-0.0186	0.0291	-0.64	0.52	0.0971	0.0649	1.50	0.13	0.0168	0.0336	0.50	0.62	0.0279	0.0250	1.12	0.26
	dominated / small	-0.0070	0.0327	-0.22	0.83	0.0165	0.0229	0.72	0.47	0.0278	0.0274	1.02	0.31	0.0006	0.0362	0.02	0.99
Research	dominator	0.0201	0.0306	0.66	0.51												
	neither / large	0.0034	0.0165	0.21	0.84	0.0453	0.0358	1.27	0.21	0.0191	0.0195	0.98	0.33	0.0228	0.0136	1.68	0.09
	dominated / small	0.0133	0.0169	0.78	0.43	0.0217	0.0122	1.78	0.08	0.0162	0.0144	1.13	0.26	0.0222	0.0196	1.13	0.26
Patents	dominator	0.0226	0.1103	0.20	0.84												
	neither / large	0.0537	0.0693	0.77	0.44	0.1022	0.1144	0.89	0.37	0.0835	0.0682	1.22	0.22	0.0633	0.0523	1.21	0.23
	dominated / small	0.0670	0.0624	1.07	0.28	0.0354	0.0505	0.70	0.48	0.0190	0.0609	0.31	0.76	-0.0840	0.0829	-1.01	0.31
Gini Dominance (D_G)																	
Dominators		0.2874	0.0439	6.54	0.00												
Dominated / Small		-0.3110	0.0343	-9.07	0.00	-0.0815	0.0487	-1.67	0.09	-0.1651	0.0354	-4.66	0.00	-0.0690	0.0367	-1.88	0.06
Dominance	dominator	0.7845	0.5995	1.31	0.19												
	neither / large	0.7545	0.4786	1.58	0.12	0.7047	0.9027	0.78	0.44	0.3516	0.5405	0.65	0.52	0.0602	0.5222	0.12	0.91
	dominated / small	0.2521	0.5891	0.43	0.67	-0.1632	0.4455	-0.37	0.71	-0.3052	0.4936	-0.62	0.54	-1.1483	0.6016	-1.91	0.06
Labor	dominator	0.6720	2.0941	0.32	0.75												
Pooling	neither / large	0.8096	1.1411	0.71	0.48	6.8112	2.9447	2.31	0.02	1.6619	1.2574	1.32	0.19	1.0483	1.0107	1.04	0.30
	dominated / small	0.2041	1.1681	0.17	0.86	2.1539	0.8407	2.56	0.01	1.6629	1.0093	1.65	0.10	3.7794	1.5524	2.43	0.02
Manufactured	dominator	-0.0311	0.0602	-0.52	0.61												
Inputs	neither / large	0.0187	0.0346	0.54	0.59	-0.1981	0.0861	-2.30	0.02	-0.0442	0.0404	-1.09	0.27	-0.0416	0.0327	-1.27	0.20
	dominated / small	0.0209	0.0380	0.55	0.58	-0.0382	0.0268	-1.42	0.15	-0.0403	0.0314	-1.28	0.20	-0.0350	0.0457	-0.77	0.44
Producer	dominator	0.0087	0.0456	0.19	0.85												
Services	neither / large	-0.0097	0.0292	-0.33	0.74	0.1185	0.0644	1.84	0.07	0.0178	0.0327	0.54	0.59	0.0140	0.0270	0.52	0.61
	dominated / small	-0.0062	0.0319	-0.19	0.85	0.0133	0.0227	0.59	0.56	0.0253	0.0267	0.95	0.34	0.0041	0.0398	0.10	0.92
Research	dominator	0.0413	0.0309	1.34	0.18												
	neither / large	0.0256	0.0168	1.52	0.13	0.0508	0.0354	1.43	0.15	0.0284	0.0195	1.45	0.15	0.0350	0.0151	2.32	0.02
	dominated / small	0.0177	0.0167	1.06	0.29	0.0219	0.0122	1.79	0.07	0.0193	0.0142	1.35	0.18	0.0056	0.0216	0.26	0.79
Patents	dominator	0.1435	0.0959	1.50	0.13												
	neither / large	0.1709	0.0602	2.84	0.00	0.1250	0.1091	1.15	0.25	0.1388	0.0610	2.27	0.02	0.0870	0.0526	1.65	0.10
	dominated / small	0.0976	0.0624	1.56	0.12	0.0617	0.0456	1.35	0.18	0.0722	0.0551	1.31	0.19	-0.0698	0.0831	-0.84	0.40

Note: "Neither" and "dominated" label the dominance models, "large" and "small" pertain to the small establishment models.

Table A.11.8. Marginal Impacts Including Plant Size Interactions for Measuring and Controlling Devices (SIC 382), 1997.

		Dominance Categories				Small ≤ 250 Employees				Small ≤ 50 Employees				Small ≤ 15 Employees			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
Concentration Ratio Dominance (D_C)																	
Dominators		0.2338	0.0453	5.16	0.00												
Dominated / Small		-0.3102	0.0355	-8.73	0.00	-0.1392	0.0596	-2.33	0.02	0.0441	0.0355	1.24	0.21	0.0701	0.0368	1.91	0.06
Dominance	dominator	-0.2194	0.2116	-1.04	0.30												
	neither / large	-0.1369	0.1660	-0.82	0.41	0.0509	0.3208	0.16	0.87	0.1055	0.1833	0.58	0.56	0.0840	0.1570	0.53	0.59
	dominated / small	-0.5347	0.2038	-2.62	0.01	-0.0320	0.1510	-0.21	0.83	-0.1519	0.1591	-0.95	0.34	-0.3804	0.2032	-1.87	0.06
Labor	dominator	-0.6915	1.4030	-0.49	0.62												
Pooling	neither / large	0.3999	0.8070	0.50	0.62	1.1181	2.1853	0.51	0.61	0.0652	0.9406	0.07	0.94	0.6430	0.6974	0.92	0.36
	dominated / small	0.7921	0.8830	0.90	0.37	0.8433	0.6447	1.31	0.19	1.1624	0.7234	1.61	0.11	0.9978	1.0687	0.93	0.35
Manufactured	dominator	0.0831	0.0375	2.21	0.03												
Inputs	neither / large	0.0389	0.0242	1.61	0.11	0.0095	0.0688	0.14	0.89	-0.0038	0.0295	-0.13	0.90	-0.0081	0.0217	-0.37	0.71
	dominated / small	-0.0022	0.0302	-0.07	0.94	-0.0055	0.0197	-0.28	0.78	-0.0006	0.0223	-0.03	0.98	0.0103	0.0328	0.31	0.75
Producer	dominator	-0.0632	0.0350	-1.81	0.07												
Services	neither / large	-0.0085	0.0233	-0.36	0.72	-0.0172	0.0542	-0.32	0.75	0.0183	0.0264	0.69	0.49	0.0113	0.0207	0.54	0.59
	dominated / small	-0.0021	0.0283	-0.08	0.94	0.0120	0.0194	0.62	0.53	0.0015	0.0224	0.07	0.95	0.0079	0.0329	0.24	0.81
Research	dominator	0.0190	0.0240	0.79	0.43												
	neither / large	0.0213	0.0139	1.53	0.13	-0.0097	0.0360	-0.27	0.79	0.0290	0.0166	1.75	0.08	0.0220	0.0121	1.82	0.07
	dominated / small	0.0109	0.0158	0.69	0.49	0.0208	0.0110	1.89	0.06	0.0118	0.0127	0.93	0.35	0.0082	0.0191	0.43	0.67
Patents	dominator	0.0527	0.0780	0.68	0.50												
	neither / large	0.1021	0.0531	1.92	0.05	0.1902	0.1210	1.57	0.12	0.0890	0.0522	1.71	0.09	0.0419	0.0432	0.97	0.33
	dominated / small	0.0687	0.0512	1.34	0.18	0.0116	0.0412	0.28	0.78	-0.0359	0.0475	-0.76	0.45	-0.0497	0.0664	-0.75	0.45
Herfindahl-Hirschman Dominance (D_H)																	
Dominators		0.2498	0.0394	6.33	0.00												
Dominated / Small		-0.2810	0.0309	-9.09	0.00	-0.1052	0.0501	-2.10	0.04	0.0629	0.0312	2.02	0.04	0.0801	0.0328	2.44	0.01
Dominance	dominator	-0.3730	0.3343	-1.12	0.26												
	neither / large	-0.3495	0.2507	-1.39	0.16	-0.4349	0.5723	-0.76	0.45	-0.0002	0.3197	0.00	1.00	0.1502	0.2600	0.58	0.56
	dominated / small	-0.6864	0.3962	-1.73	0.08	0.0285	0.2459	0.12	0.91	-0.1160	0.2568	-0.45	0.65	-0.5229	0.3396	-1.54	0.12
Labor	dominator	-0.3858	1.4197	-0.27	0.79												
Pooling	neither / large	0.4619	0.8063	0.57	0.57	1.9183	2.2036	0.87	0.38	0.2776	0.9512	0.29	0.77	0.7261	0.6905	1.05	0.29
	dominated / small	0.7960	0.8866	0.90	0.37	0.8799	0.6361	1.38	0.17	1.1949	0.7199	1.66	0.10	1.0970	1.0741	1.02	0.31
Manufactured	dominator	0.0692	0.0400	1.73	0.08												
Inputs	neither / large	0.0393	0.0245	1.61	0.11	-0.0442	0.0708	-0.62	0.53	-0.0079	0.0300	-0.26	0.79	-0.0100	0.0215	-0.46	0.64
	dominated / small	0.0044	0.0305	0.14	0.89	-0.0044	0.0195	-0.23	0.82	0.0035	0.0223	0.16	0.88	0.0142	0.0329	0.43	0.67
Producer	dominator	-0.0666	0.0348	-1.91	0.06												
Services	neither / large	-0.0124	0.0231	-0.54	0.59	-0.0056	0.0527	-0.11	0.92	0.0161	0.0261	0.62	0.54	0.0070	0.0202	0.35	0.73
	dominated / small	-0.0116	0.0278	-0.42	0.68	0.0073	0.0189	0.39	0.70	-0.0039	0.0220	-0.18	0.86	0.0043	0.0327	0.13	0.89
Research	dominator	0.0266	0.0247	1.08	0.28												
	neither / large	0.0225	0.0139	1.62	0.10	-0.0076	0.0357	-0.21	0.83	0.0285	0.0165	1.73	0.08	0.0260	0.0119	2.18	0.03
	dominated / small	0.0165	0.0155	1.06	0.29	0.0249	0.0108	2.31	0.02	0.0166	0.0125	1.33	0.18	0.0110	0.0192	0.57	0.57
Patents	dominator	0.0383	0.0830	0.46	0.64												
	neither / large	0.0715	0.0563	1.27	0.20	0.2346	0.1248	1.88	0.06	0.0655	0.0542	1.21	0.23	0.0247	0.0461	0.54	0.59
	dominated / small	0.0448	0.0524	0.85	0.39	-0.0021	0.0441	-0.05	0.96	-0.0518	0.0504	-1.03	0.30	-0.0661	0.0680	-0.97	0.33

Note: "Neither" and "dominated" label the dominance models, "large" and "small" pertain to the small establishment models.

Table A.11.8. Marginal Impacts Including Plant Size Interactions for Measuring and Controlling Devices (SIC 382), 1997, continued.

		Dominance Categories				Small ≤ 250 Employees				Small ≤ 50 Employees				Small ≤ 15 Employees			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
Rosenbluth Dominance (D_R)																	
Dominators		0.2198	0.0445	4.94	0.00												
Dominated / Small		-0.2770	0.0293	-9.45	0.00	-0.1056	0.0532	-1.98	0.05	0.0642	0.0316	2.03	0.04	0.0814	0.0326	2.49	0.01
Dominance	dominator	-1.8172	0.6336	-2.87	0.00												
	neither / large	-1.3102	0.6401	-2.05	0.04	-1.0165	1.3444	-0.76	0.45	-0.1302	0.7732	-0.17	0.87	0.0957	0.6733	0.14	0.89
	dominated / small	-1.8468	0.9099	-2.03	0.04	-0.1496	0.6399	-0.23	0.82	-0.3671	0.6674	-0.55	0.58	-0.8903	0.8175	-1.09	0.28
Labor	dominator	-0.9206	1.4090	-0.65	0.51												
Pooling	neither / large	0.3089	0.8044	0.38	0.70	0.6478	2.1893	0.30	0.77	0.0540	0.9312	0.06	0.95	0.6075	0.6835	0.89	0.37
	dominated / small	0.6199	0.8639	0.72	0.47	0.7140	0.6288	1.14	0.26	1.0189	0.7104	1.43	0.15	0.6696	1.0599	0.63	0.53
Manufactured	dominator	0.0704	0.0381	1.85	0.06												
Inputs	neither / large	0.0356	0.0239	1.49	0.14	-0.0025	0.0672	-0.04	0.97	-0.0093	0.0293	-0.32	0.75	-0.0096	0.0212	-0.46	0.65
	dominated / small	0.0086	0.0297	0.29	0.77	-0.0057	0.0192	-0.30	0.77	0.0021	0.0221	0.10	0.92	0.0147	0.0326	0.45	0.65
Producer	dominator	-0.0685	0.0352	-1.94	0.05												
Services	neither / large	-0.0094	0.0233	-0.40	0.69	-0.0169	0.0537	-0.31	0.75	0.0166	0.0261	0.64	0.53	0.0067	0.0206	0.33	0.74
	dominated / small	-0.0132	0.0278	-0.47	0.64	0.0061	0.0192	0.32	0.75	-0.0055	0.0225	-0.25	0.81	-0.0037	0.0332	-0.11	0.91
Research	dominator	0.0178	0.0237	0.75	0.45												
	neither / large	0.0232	0.0137	1.70	0.09	-0.0165	0.0357	-0.46	0.64	0.0288	0.0161	1.79	0.07	0.0250	0.0117	2.14	0.03
	dominated / small	0.0147	0.0153	0.97	0.33	0.0258	0.0107	2.42	0.02	0.0178	0.0124	1.43	0.15	0.0184	0.0189	0.97	0.33
Patents	dominator	-0.0393	0.0810	-0.49	0.63												
	neither / large	0.0572	0.0521	1.10	0.27	0.2102	0.1238	1.70	0.09	0.0834	0.0523	1.59	0.11	0.0302	0.0428	0.71	0.48
	dominated / small	0.0358	0.0497	0.72	0.47	0.0020	0.0400	0.05	0.96	-0.0446	0.0465	-0.96	0.34	-0.0496	0.0660	-0.75	0.45
Gini Dominance (D_G)																	
Dominators		0.2832	0.0368	7.69	0.00												
Dominated / Small		-0.2849	0.0288	-9.90	0.00	-0.1231	0.0462	-2.66	0.01	0.0721	0.0300	2.40	0.02	0.1023	0.0304	3.37	0.00
Dominance	dominator	1.2329	0.4622	2.67	0.01												
	neither / large	0.8229	0.3450	2.39	0.02	0.2553	0.9739	0.26	0.79	0.8834	0.4040	2.19	0.03	0.7174	0.3342	2.15	0.03
	dominated / small	0.8935	0.4476	2.00	0.05	0.5916	0.3194	1.85	0.06	0.3471	0.3445	1.01	0.31	0.0696	0.4579	0.15	0.88
Labor	dominator	-0.8597	1.4176	-0.61	0.54												
Pooling	neither / large	0.4902	0.8015	0.61	0.54	0.3019	2.2556	0.13	0.89	0.1310	0.9266	0.14	0.89	0.6394	0.6806	0.94	0.35
	dominated / small	0.9282	0.8842	1.05	0.29	0.7882	0.6271	1.26	0.21	1.0679	0.7117	1.50	0.13	0.8448	1.0640	0.79	0.43
Manufactured	dominator	0.0416	0.0397	1.05	0.29												
Inputs	neither / large	0.0186	0.0243	0.77	0.44	0.0049	0.0667	0.07	0.94	-0.0094	0.0296	-0.32	0.75	-0.0089	0.0216	-0.41	0.68
	dominated / small	0.0053	0.0305	0.17	0.86	-0.0076	0.0197	-0.39	0.70	0.0024	0.0223	0.11	0.91	0.0114	0.0324	0.35	0.72
Producer	dominator	-0.0679	0.0360	-1.89	0.06												
Services	neither / large	-0.0158	0.0230	-0.68	0.49	-0.0125	0.0524	-0.24	0.81	0.0138	0.0258	0.54	0.59	0.0013	0.0200	0.06	0.95
	dominated / small	-0.0224	0.0268	-0.83	0.40	0.0054	0.0186	0.29	0.77	-0.0062	0.0217	-0.29	0.77	0.0028	0.0324	0.09	0.93
Research	dominator	0.0478	0.0245	1.95	0.05												
	neither / large	0.0332	0.0134	2.48	0.01	-0.0059	0.0332	-0.18	0.86	0.0275	0.0158	1.74	0.08	0.0223	0.0115	1.95	0.05
	dominated / small	0.0213	0.0148	1.44	0.15	0.0235	0.0103	2.28	0.02	0.0147	0.0119	1.24	0.21	0.0183	0.0177	1.03	0.30
Patents	dominator	0.1373	0.0690	1.99	0.05												
	neither / large	0.1634	0.0486	3.36	0.00	0.2890	0.1157	2.50	0.01	0.0863	0.0477	1.81	0.07	0.0277	0.0398	0.70	0.49
	dominated / small	0.0897	0.0500	1.80	0.07	0.0186	0.0386	0.48	0.63	-0.0203	0.0447	-0.46	0.65	-0.0125	0.0632	-0.20	0.84

Note: "Neither" and "dominated" label the dominance models, "large" and "small" pertain to the small establishment models.

Table A.11.9. Marginal Impacts Including Plant Size Interactions for Measuring and Controlling Devices (SIC 382), 2002.

		Dominance Categories				Small ≤ 250 Employees				Small ≤ 50 Employees				Small ≤ 15 Employees			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
Concentration Ratio Dominance (D_C)																	
Dominators		0.2789	0.0472	5.91	0.00												
Dominated / Small		-0.1849	0.0392	-4.72	0.00	-0.1025	0.0623	-1.65	0.10	0.0149	0.0387	0.38	0.70	0.0641	0.0424	1.51	0.13
Dominance	dominator	0.0995	0.2436	0.41	0.68												
	neither / large	0.1667	0.1906	0.87	0.38	-0.3288	0.3592	-0.92	0.36	0.0722	0.2182	0.33	0.74	-0.0432	0.1980	-0.22	0.83
	dominated / small	0.1824	0.2624	0.70	0.49	0.0544	0.1884	0.29	0.77	0.0218	0.1959	0.11	0.91	0.0556	0.2254	0.25	0.81
Labor	dominator	-2.6861	1.6870	-1.59	0.11												
Pooling	neither / large	-1.1657	1.2206	-0.96	0.34	0.8088	2.2595	0.36	0.72	0.6876	1.1926	0.58	0.56	0.8094	0.9749	0.83	0.41
	dominated / small	0.4882	1.1892	0.41	0.68	0.7021	0.9332	0.75	0.45	1.0152	1.0423	0.97	0.33	1.2422	1.4418	0.86	0.39
Manufactured	dominator	0.0096	0.0413	0.23	0.82												
Inputs	neither / large	-0.0131	0.0295	-0.44	0.66	-0.0910	0.0637	-1.43	0.15	-0.0306	0.0333	-0.92	0.36	-0.0334	0.0256	-1.30	0.19
	dominated / small	0.0136	0.0357	0.38	0.70	-0.0321	0.0236	-1.36	0.17	-0.0377	0.0268	-1.41	0.16	-0.0546	0.0374	-1.46	0.14
Producer	dominator	-0.0672	0.0441	-1.52	0.13												
Services	neither / large	-0.0090	0.0310	-0.29	0.77	-0.0301	0.0615	-0.49	0.62	0.0012	0.0324	0.04	0.97	0.0199	0.0263	0.76	0.45
	dominated / small	-0.0395	0.0346	-1.14	0.25	0.0188	0.0251	0.75	0.45	0.0245	0.0289	0.85	0.40	0.0083	0.0409	0.20	0.84
Research	dominator	0.0118	0.0249	0.47	0.64												
	neither / large	0.0199	0.0178	1.12	0.26	0.0066	0.0326	0.20	0.84	0.0180	0.0183	0.99	0.32	0.0069	0.0148	0.46	0.64
	dominated / small	0.0042	0.0181	0.23	0.82	0.0107	0.0140	0.76	0.44	0.0036	0.0159	0.23	0.82	0.0233	0.0216	1.08	0.28
Patents	dominator	0.2442	0.0776	3.15	0.00												
	neither / large	0.0632	0.0531	1.19	0.23	0.1877	0.1154	1.63	0.10	0.0401	0.0559	0.72	0.47	0.0232	0.0468	0.50	0.62
	dominated / small	0.0033	0.0616	0.05	0.96	0.0111	0.0444	0.25	0.80	0.0139	0.0500	0.28	0.78	0.0420	0.0667	0.63	0.53
Herfindahl-Hirschman Dominance (D_H)																	
Dominators		0.2525	0.0509	4.96	0.00												
Dominated / Small		-0.1946	0.0386	-5.04	0.00	-0.1084	0.0627	-1.73	0.08	0.0134	0.0401	0.33	0.74	0.0414	0.0431	0.96	0.34
Dominance	dominator	0.3008	0.3278	0.92	0.36												
	neither / large	0.4930	0.2992	1.65	0.10	-0.1980	0.6655	-0.30	0.77	0.2038	0.3610	0.56	0.57	0.3404	0.3032	1.12	0.26
	dominated / small	0.5160	0.4544	1.14	0.26	0.3355	0.2826	1.19	0.24	0.2450	0.3037	0.81	0.42	-0.0051	0.3854	-0.01	0.99
Labor	dominator	-2.1192	1.7641	-1.20	0.23												
Pooling	neither / large	-1.0534	1.2453	-0.85	0.40	1.3123	2.3951	0.55	0.58	1.0201	1.1895	0.86	0.39	0.8703	0.9514	0.91	0.36
	dominated / small	1.1482	1.1591	0.99	0.32	0.9446	0.9034	1.05	0.30	1.2509	1.0201	1.23	0.22	1.7628	1.4417	1.22	0.22
Manufactured	dominator	0.0199	0.0415	0.48	0.63												
Inputs	neither / large	-0.0115	0.0297	-0.39	0.70	-0.0873	0.0635	-1.38	0.17	-0.0283	0.0330	-0.86	0.39	-0.0367	0.0251	-1.46	0.14
	dominated / small	0.0025	0.0352	0.07	0.94	-0.0365	0.0231	-1.58	0.11	-0.0442	0.0263	-1.68	0.09	-0.0558	0.0372	-1.50	0.13
Producer	dominator	-0.0562	0.0441	-1.27	0.20												
Services	neither / large	-0.0055	0.0314	-0.18	0.86	-0.0250	0.0626	-0.40	0.69	0.0028	0.0326	0.09	0.93	0.0230	0.0265	0.87	0.39
	dominated / small	-0.0311	0.0348	-0.89	0.37	0.0235	0.0255	0.92	0.36	0.0253	0.0293	0.86	0.39	0.0145	0.0414	0.35	0.73
Research	dominator	0.0008	0.0252	0.03	0.98												
	neither / large	0.0134	0.0177	0.76	0.45	0.0037	0.0334	0.11	0.91	0.0130	0.0183	0.71	0.48	0.0038	0.0147	0.26	0.80
	dominated / small	-0.0018	0.0179	-0.10	0.92	0.0068	0.0139	0.49	0.62	0.0029	0.0158	0.18	0.85	0.0163	0.0216	0.75	0.45
Patents	dominator	0.2594	0.0785	3.31	0.00												
	neither / large	0.1043	0.0532	1.96	0.05	0.1721	0.1161	1.48	0.14	0.0296	0.0538	0.55	0.58	0.0359	0.0442	0.81	0.42
	dominated / small	0.0534	0.0565	0.94	0.34	0.0220	0.0420	0.52	0.60	0.0278	0.0476	0.58	0.56	0.0205	0.0645	0.32	0.75

Note: "Neither" and "dominated" label the dominance models, "large" and "small" pertain to the small establishment models.

Table A.11.9. Marginal Impacts Including Plant Size Interactions for Measuring and Controlling Devices (SIC 382), 2002, continued.

		Dominance Categories				Small ≤ 250 Employees				Small ≤ 50 Employees				Small ≤ 15 Employees			
		Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value	Coeff.	Std. Err.	t Stat.	p Value
Rosenbluth Dominance (D_R)																	
Dominators		0.2839	0.0525	5.41	0.00												
Dominated / Small		-0.2003	0.0370	-5.41	0.00	-0.1113	0.0603	-1.85	0.06	0.0189	0.0385	0.49	0.62	0.0489	0.0421	1.16	0.25
Dominance	dominator	0.4409	0.6276	0.70	0.48												
	neither / large	0.6857	0.6229	1.10	0.27	-1.6178	1.1993	-1.35	0.18	-0.3089	0.7183	-0.43	0.67	0.1689	0.6184	0.27	0.78
	dominated / small	-0.0940	0.9116	-0.10	0.92	0.2047	0.5874	0.35	0.73	0.2247	0.6269	0.36	0.72	-0.0806	0.7648	-0.11	0.92
Labor	dominator	-2.8047	1.7715	-1.58	0.11												
Pooling	neither / large	-0.9541	1.2175	-0.78	0.43	1.5917	2.2889	0.70	0.49	1.2309	1.1996	1.03	0.31	0.6153	0.9762	0.63	0.53
	dominated / small	0.6278	1.1573	0.54	0.59	0.6094	0.9347	0.65	0.51	0.8330	1.0517	0.79	0.43	1.6208	1.4726	1.10	0.27
Manufactured	dominator	0.0204	0.0420	0.49	0.63												
Inputs	neither / large	-0.0074	0.0297	-0.25	0.80	-0.0826	0.0638	-1.29	0.20	-0.0298	0.0333	-0.90	0.37	-0.0246	0.0254	-0.97	0.33
	dominated / small	0.0179	0.0351	0.51	0.61	-0.0235	0.0233	-1.01	0.31	-0.0260	0.0264	-0.98	0.33	-0.0493	0.0373	-1.32	0.19
Producer	dominator	-0.0786	0.0451	-1.74	0.08												
Services	neither / large	-0.0104	0.0310	-0.34	0.74	-0.0586	0.0622	-0.94	0.35	-0.0050	0.0326	-0.15	0.88	0.0058	0.0263	0.22	0.83
	dominated / small	-0.0488	0.0343	-1.42	0.15	0.0072	0.0250	0.29	0.78	0.0066	0.0289	0.23	0.82	0.0018	0.0414	0.04	0.97
Research	dominator	0.0089	0.0247	0.36	0.72												
	neither / large	0.0160	0.0174	0.92	0.36	0.0078	0.0329	0.24	0.81	0.0165	0.0180	0.92	0.36	0.0093	0.0143	0.65	0.52
	dominated / small	0.0027	0.0177	0.15	0.88	0.0120	0.0135	0.89	0.37	0.0081	0.0155	0.53	0.60	0.0222	0.0214	1.04	0.30
Patents	dominator	0.2728	0.0820	3.33	0.00												
	neither / large	0.0878	0.0535	1.64	0.10	0.1062	0.1164	0.91	0.36	0.0101	0.0549	0.18	0.85	0.0285	0.0450	0.63	0.53
	dominated / small	0.0497	0.0566	0.88	0.38	0.0176	0.0424	0.42	0.68	0.0237	0.0486	0.49	0.63	0.0295	0.0672	0.44	0.66
Gini Dominance (D_G)																	
Dominators		0.2789	0.0452	6.17	0.00												
Dominated / Small		-0.1817	0.0353	-5.14	0.00	-0.1491	0.0572	-2.61	0.01	-0.0041	0.0366	-0.11	0.91	0.0908	0.0369	2.46	0.01
Dominance	dominator	0.8234	0.4319	1.91	0.06												
	neither / large	0.5073	0.3364	1.51	0.13	0.7001	0.9251	0.76	0.45	0.5471	0.3835	1.43	0.15	0.0285	0.3143	0.09	0.93
	dominated / small	-0.5641	0.4278	-1.32	0.19	-0.1222	0.2952	-0.41	0.68	-0.3796	0.3286	-1.16	0.25	-0.3086	0.4401	-0.70	0.48
Labor	dominator	-1.2828	1.7247	-0.74	0.46												
Pooling	neither / large	-0.1333	1.1964	-0.11	0.91	1.2361	2.1785	0.57	0.57	1.7748	1.1947	1.49	0.14	1.8233	0.9744	1.87	0.06
	dominated / small	1.5973	1.1360	1.41	0.16	1.8973	0.9355	2.03	0.04	2.2960	1.0378	2.21	0.03	2.6251	1.4249	1.84	0.07
Manufactured	dominator	0.0057	0.0415	0.14	0.89												
Inputs	neither / large	-0.0086	0.0302	-0.29	0.78	-0.0904	0.0648	-1.39	0.16	-0.0303	0.0340	-0.89	0.37	-0.0232	0.0261	-0.89	0.38
	dominated / small	0.0091	0.0358	0.25	0.80	-0.0227	0.0246	-0.92	0.36	-0.0268	0.0277	-0.97	0.33	-0.0383	0.0386	-0.99	0.32
Producer	dominator	-0.0515	0.0434	-1.19	0.24												
Services	neither / large	-0.0151	0.0319	-0.47	0.64	-0.0353	0.0618	-0.57	0.57	-0.0012	0.0330	-0.04	0.97	0.0151	0.0270	0.56	0.58
	dominated / small	-0.0398	0.0354	-1.12	0.26	0.0146	0.0263	0.55	0.58	0.0182	0.0300	0.61	0.54	0.0039	0.0424	0.09	0.93
Research	dominator	0.0142	0.0254	0.56	0.58												
	neither / large	0.0220	0.0182	1.21	0.23	0.0119	0.0322	0.37	0.71	0.0127	0.0184	0.69	0.49	-0.0008	0.0150	-0.05	0.96
	dominated / small	0.0066	0.0176	0.38	0.71	0.0051	0.0143	0.36	0.72	0.0010	0.0161	0.06	0.95	0.0167	0.0218	0.76	0.45
Patents	dominator	0.2175	0.0749	2.91	0.00												
	neither / large	0.0536	0.0519	1.03	0.30	0.2149	0.1003	2.14	0.03	0.0330	0.0521	0.63	0.53	0.0395	0.0439	0.90	0.37
	dominated / small	0.0361	0.0548	0.66	0.51	0.0154	0.0422	0.36	0.72	0.0209	0.0473	0.44	0.66	0.0094	0.0621	0.15	0.88

Note: "Neither" and "dominated" label the dominance models, "large" and "small" pertain to the small establishment models.

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