OCCUPATIONAL MOBILITY, GENDER AND CLASS IN THE UNITED STATES, 1965-2015

Jessica Anne Pearlman

A dissertation submitted to the faculty at University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Sociology in the College of Arts and Sciences.

Chapel Hill
2016

Approved by:
Arne Kalleberg
Philip Cohen
Guang Guo
Ted Mouw
Lisa Pearce
This dissertation consists of three papers. The first paper examines the impact of inter-firm mobility on wage trajectories of three birth cohorts of young male workers, focusing on how the relationship between mobility and wages has changed from 1965-2013. A key element of this analysis is exploring how occupational mobility might moderate the impact of inter-firm mobility on wages. A second element of this analysis examines how educational attainment moderates the impact of inter-firm mobility on wages and how this may have changed over time, concurrent with rising wage returns to education. The second paper also examines the relationship between inter-firm mobility and wages and the extent to which occupational mobility and educational attainment might moderate this impact. The second paper takes a life course perspective, examining a single cohort of men and women from ages 18-55, over the years 1979-2012. This paper explores the extent to which the relationships between inter-firm mobility, occupational mobility, education and wages vary over the life course, as a function of the duration of time since the mobility event and between men and women. This paper also explores the extent to which gender differences are due to the behavior and treatment of individual women and men as well as opposed to their occupational location in the labor market. The third paper examines the extent to which mobility by women between occupations with different levels of female representation have changed over time since 1965. The paper explores
transitions between ‘male dominated’, female dominated’ and ‘integrated’ occupations as well as transitions between occupations of any degree of gender representation to other occupations with a varying greater or lesser degrees of gender representation than the first. The paper uses 4 birth cohorts of women, with a range of birth years from 1923-1984, analyzing data from 1965-2013. The paper analyzes the extent to which the probability of the various transitions as well as the relationship between education level and the probability of specific transitions has changed over time. In addition, the paper explores the relationship between macro-economic conditions and the likelihood of these transitions.
For Mom, Dad, Aunt Betty and Miguel
ACKNOWLEDGEMENTS

This dissertation could not have been completed without the guidance and support of many people. Much gratitude to my adviser, Arne Kalleberg, who had the uncanny ability to help me to transform my complicated set of research interests into a coherent dissertation topic and set of research questions and whose vast knowledge of and own incredibly comprehensive and creative theoretical framework for understanding the changes in the United States labor market over the past 50 years informs each piece of this dissertation. Many thanks also to my dissertation committee: Ted Mouw, whose boundless knowledge of both statistical methods and the literature on labor market stratification was enormously helpful, provided guidance that was instrumental in developing and operationalizing a theoretical framework for occupational mobility for this dissertation. Ted’s own work also serves as an example for me of research of the highest levels of rigor and quality. Philip Cohen’s expertise and ideas were invaluable in guiding the development of the framework for gender inequality in the labor market used in this dissertation; his careful treatment of the concept of occupational mobility also helped me to operationalize this concept in a much fuller way. In addition, Philip’s own research modeled for me incredibly creative ways to use and interpret quantitative methods to illustrate theoretical concepts. I have learned a tremendous amount from Lisa Pearce about the distinguishing elements of a valuable research topic and quality research paper. Lisa’s substantive expertise on adolescent development and family also enabled me make linkages between the findings of this dissertation to a much broader research context. Thanks also to Lisa for many opportunities to participate in research projects on a variety of very interesting topics as well as for re-kindling
my interest in Nepal. It would have been impossible for me to use the methods applied in this dissertation without Guang Guo’s expertise and research contributions on event history models; he also helped me several times to recognize my own methodological assumptions to develop a more comprehensive tool kit.

Needless to say, this research could not have been conducted without the respondents of the four waves of the NLS surveys, who generously gave their time to answer the survey questions year after year. Many thanks also to the staff of the NLS Surveys who created the surveys, interviewed respondents, and transformed the data into a very user-friendly format. Special thanks to Steve McClaskie of NLS User Services for patiently answering numerous questions.

Thanks to Jan Hendrickson-Smith, Cathy Zimmer, Chris Wiesen, Howard Aldrich, Ken Bollen, David Guilkey, Tom Mroz, Jennie Brand, Matt Huffman, Dirgha Ghimire, Prem Bhandari, and the entire staffs of the UNC Departments of Sociology and Statistics, the Odum Institute, the Carolina Population Center, and ISER at the University of Michigan and in the Chitwan Valley, Nepal.

My graduate school experience has been greatly enhanced by attending UNC with a fantastic group of graduate students and post-doctoral scholars. In order to not make my acknowledgements longer than the dissertation itself, I have left off individual messages but I feel lucky to have known each of you, especially Mike Aguilar, Augustus Anderson, Daniel Auguste, Heather Ba, Sierra Bainter, Shawn Bauldry, Loren Berlin, Joe Bongiovi, Colin Campbell, Raquel Coutinho, Kristen Downs, Josh Drucker, Mike Dunn, Heather Edelblute, Shane Elliott, Jason Freeman, Annelies Goger, Shelley Golden, Aiko Hattori, George Merlin Hayward, Jonathan Horowitz, Anne Hunter, Karam Hwang, Elyse Jennings, Jason Jolley,
Jonathan Kropko, Emily McKendry-Smith Jennifer Miller, Cheryl Roberts, Rosemary Russo, Andy Sharma, Jane Lee Song, Ashton Verdery, Phil Weickert, Nathalie Williams, and Tiantian Yang.
TABLE OF CONTENTS

LIST OF TABLES .................................................................................................................... xiii

LIST OF FIGURES ................................................................................................................ xiv

CHAPTER 1: INTRODUCTION TO DISSERTATION ............................................................... 1

Background Context ........................................................................................................... 1

Paper 1: Should I Stay or Should I Go? The Impact of Firm Changes, Occupational Mobility and Education on Earnings, 1965-2015 ...................................................................................... 2

Paper 2: Should She Go or Should He? Gender Differences in the Impact of Firm Changes, Occupational Mobility and Education on Earnings across the Life Course, 1965-2015 .................................................................................. 3

Paper 3: Has the Revolving Door Shut?: Women’s Occupational Mobility and Occupational Segregation, 1965-2015 .......................................................................................... 5

Overall Themes Linking the Three Papers ......................................................................... 7

Occupation Specific Human Capital ............................................................................... 7

Lack of Benefits from Job Mobility among Less Well Educated Workers ..................... 8

Occupational Segregation among Highly Educated Women ........................................... 9

CHAPTER 2: SHOULD I STAY OR SHOULD I GO? THE IMPACT OF FIRM CHANGES, OCCUPATIONAL MOBILITY AND EDUCATION ON EARNINGS, 1965-2015 ............. 10

Introduction ......................................................................................................................... 1

Literature Review ................................................................................................................ 12

Inter-Firm Mobility: Theory ............................................................................................... 12

Inter-Firm Mobility: Results ............................................................................................... 14

Inter-Firm Mobility: Changes over Time ............................................................................ 16

Occupational Mobility: Theory ......................................................................................... 18

Introduction.................................................................61

Literature Review..........................................................62

Inter-Firm Mobility: Age at which the Mobility Occurs.................62

Inter-Firm Mobility and Wages: Duration of Time since the Mobility Event……64

Voluntary Inter-Firm Mobility: Gender Differences: Theory..................65

Involuntary Inter-Firm Mobility: Gender Differences: Theory...............70

Inter-Firm Mobility: Gender Differences: Results........................70
Summary on Inter-Firm and Occupational Mobility by Gender, Age and Time Since Mobility ................................................................. 72
Research Questions ........................................................................... 73
Data and Methods ............................................................................ 73
   Sample .......................................................................................... 73
   Variables ....................................................................................... 74
   Analysis Technique ....................................................................... 78
Results .............................................................................................. 83
   Descriptive Statistics ................................................................. 83
   Regression Results ..................................................................... 84
   Involuntary Job Loss ................................................................. 84
   Voluntary Inter-Firm Mobility: Age and Duration Since Mobility .......... 86
   Voluntary Inter-Firm Mobility: Gender Differences ......................... 89
   Summary of Key Findings ............................................................ 92
Discussion and Conclusion ............................................................. 92

CHAPTER 4: HAS THE REVOLVING DOOR SHUT?: WOMEN’S OCCUPATIONAL
MOBILITY AND OCCUPATIONAL SEGREGATION, 1965-2015 ......................... 111
Introduction .................................................................................. 111
Literature Review .......................................................................... 113
   Occupational Segregation by Gender ........................................ 113
   Revolving Door Theory ............................................................ 114
   Applications of the Revolving Door Theory ............................... 115
Summary of Mobility between Male and Female Dominated Occupations .... 120
Research Questions ...................................................................... 120
Data and Methods.............................................................................................................................121
Sample...............................................................................................................................................121
Variables...........................................................................................................................................122
Analysis Technique............................................................................................................................125
Modeling Strategies............................................................................................................................129
Additional Modeling Issues................................................................................................................131
Results...............................................................................................................................................136
Descriptive Statistics..........................................................................................................................137
Regression Results: Six Category Outcome.........................................................................................139
Regression Results: Four Category Outcome.......................................................................................141
Summary of Key Findings....................................................................................................................150
Discussion and Conclusion..................................................................................................................150
Addendum to Chapter 3: Random Effects Models............................................................................153
APPENDIX: ADDITIONAL FIGURES FOR CHAPTER 4................................................................179
REFERENCES....................................................................................................................................204
LIST OF TABLES

Table 2.1 – Descriptive Statistics .................................................................50
Table 2.2 – Regression Models: Original Cohort ........................................51
Table 2.3 – Regression Models: Middle Cohort ........................................52
Table 2.4 – Regression Models: Recent Cohort ........................................53
Table 2.5 – Impact on Wages and Log Wages ...........................................54
Table 3.1 – Prevalence of Inter-Firm Mobility Using One and Two Year Intervals ..........96
Table 3.2 – Descriptive Statistics .................................................................99
Table 3.3 – Regression Models .................................................................100
Table 3.4 – Regression Models with Tenure Controls ................................101
Table 3.5 – Regression Models with Occupation Fraction Female ...........102
Table 4.1 – Matched Pairs of Two Year Intervals .......................................156
Table 4.2 – Descriptive Statistics .................................................................160
Table 4.3 – Change in Fraction Female .......................................................161
Table 4.4 – Occupational Transitions, Originated Male Dominated Occupation ..163
Table 4.5 – Occupational Transitions, Originated Integrated Occupation ........164
Table 4.6 – Occupational Transitions, Originated Female Dominated Occupation ..165
Table 4.7 – Occupational Transitions, Originated Male Dominated Occupation, RE ...175
Table 4.8 – Occupational Transitions, Originated Integrated Occupation, RE ....176
Table 4.9 – Occupational Transitions, Originated Female Dominated Occupation, RE ...177
Table 4.10 – Ratio of Coefficients ..............................................................178
LIST OF FIGURES

Figure 2.1 – Conceptual Framework.................................................................48

Figure 2.2 – Percentage of Respondents with at least One Experience of Firm Mobility by Type.................................................................49

Figure 2.3 – Impact of Involuntary Mobility on Log Wages .........................55

Figure 2.4 – Impact of Involuntary Job Loss on Log Wages: Total Effect and Net of Tenure.........................................................................................56

Figure 2.5 – Impact of Voluntary Firm Mobility on Log Wages........................57

Figure 2.6 – Impact of Voluntary Firm Mobility on Log Wages: Total Effect and Net of Tenure.........................................................................................58

Figure 2.7 – Impact of Voluntary Occupation Change for Individuals without a BA.............59

Figure 2.8 – Occupation Skill Differences and the Impact of Occupational Mobility.........................60

Figure 3.1 – Conceptual Framework.................................................................95

Figure 3.2 – Percentage of Respondents with at least One Involuntary Mobility Event by Type.........................................................................................97

Figure 3.3 – Percentage of Respondents with at least One Voluntary Mobility Event by Type.........................................................................................98

Figure 3.4 – Impact of Displacement on Wages in the Year of Displacement..............104

Figure 3.5 – Impact of Displacement w/ New Occupation on Wages in Year of Displacement.........................................................................................105

Figure 3.6 – Impact of Voluntary Inter-Firm Mobility on Wages for Individuals without a BA.................................................................106

Figure 3.7 – Impact of Voluntary Inter-Firm Mobility for Individuals without a BA: Model 2.................................................................107

Figure 3.8 – Impact of Voluntary Mobility on Log Wages for Individuals with a BA..........108

Figure 3.9 – Impact of Voluntary Firm Mobility on Wages: Gender Differences..............109

Figure 3.10 – Impact of Voluntary Firm Mobility for Individuals with a BA: Percent Female.........................................................................................110
Figure 4.1 – Mean and Median Percentage Female in Women's Occupations .................. 157
Figure 4.2 – Percent of Women in Occupation Categories over Time .......................... 158
Figure 4.3 – Percent of Labor Force in Occupation Categories over Time .................... 159
Figure 4.4 – Probability of Occupational Transitions by Year and Model ..................... 162
Figure 4.5 – Probability of Occupational Transitions by Year and Occupation Gender Representation Category of Origin, Net of Age ............................. 166
Figure 4.6 – Probability of Occupational Transitions by Year and Occupation Gender Representation Category of Origin, Net of National Occupational Distribution and Age ....................................................... 167
Figure 4.7 – Probability of Occupational Transitions by Year and Model, Originated Male Dominated Occupation ................................................................. 168
Figure 4.8 – Probability of Occupational Transitions by Year and Model, Originated Integrated Occupation ................................................................. 169
Figure 4.9 – Probability of Occupational Transitions by Year and Model, Originated Female Dominated Occupation ................................................................. 170
Figure 4.10 – Probabilities of Occupational Transitions by Year and Education Level (Model 4): Originated Male Dominated Occupation .................................................. 171
Figure 4.11 – Probabilities of Occupational Transitions by Year and Education Level (Model 4): Originated Integrated Occupation .................................................. 172
Figure 4.12 – Probabilities of Occupational Transitions by Year and Education Level (Model 4): Originated Female Dominated Occupation .................................................. 173
Figure 4.13 – Impact of Unemployment Rate on Probability of Occupation Transitions (Model 4 Coefficients) ................................................................. 174

Figure A.1 - Labor Market Characteristics over Time ................................................. 179
Figure A.2 - Transition Percentages by Year: Originated Male Dominated Occupation ................................................................. 180
Figure A.3 - Transition Percentages by Year: Originated Integrated Occupation ............. 181
Figure A.4 - Transition Percentages by Year: Originated Female Dominated Occupation ................................................................. 182
Figure A.5 - Transition Percentages by Year .................................................................183

Figure A.6 - Transition Percentages by Age: Early Cohort, Originated Male
Dominated Occupation ............................................................................................184

Figure A.7 - Transition Percentages by Age: Early Cohort, Originated
Integrated Occupation ............................................................................................185

Figure A.8 - Transition Percentages by Age: Early Cohort, Originated Female
Dominated Occupation ............................................................................................186

Figure A.9 - Transition Percentages by Age: Original Cohort, Originated Male
Dominated Occupation ............................................................................................187

Figure A.10 - Transition Percentages by Age: Original Cohort, Originated Integrated
Occupation ................................................................................................................188

Figure A.11 - Transition Percentages by Age: Original Cohort, Originated Female
Dominated Occupation ............................................................................................189

Figure A.12 - Transition Percentages by Age: Middle Cohort, Originated Male
Dominated Occupation ............................................................................................190

Figure A.13 - Transition Percentages by Age: Middle Cohort, Originated Integrated
Occupation ................................................................................................................191

Figure A.14 - Transition Percentages by Age: Middle Cohort, Originated Female
Dominated Occupation ............................................................................................192

Figure A.15 - Transition Percentages by Age: Recent Cohort, Originated
Male Dominated Occupation ....................................................................................193

Figure A.16 - Transition Percentages by Age: Recent Cohort, Originated
Integrated Occupation ............................................................................................194

Figure A.17 - Transition Percentages by Age: Recent Cohort, Originated Female
 Dominated Occupation ............................................................................................195

Figure A.18 - Transition Percentages by Age: Early Cohort ........................................196

Figure A.19 - Transition Percentages by Age: Original Cohort .....................................197

Figure A.20 - Transition Percentage by Age: Middle Cohort .......................................198

Figure A.21 - Transition Percentages by Age: Recent Cohort .......................................199
Figure A.22 - Transition Percentages by Years in Occupation, Originated Male Dominated Occupation

Figure A.23 - Transition Percentages by Years in Occupation, Originated Integrated Occupation

Figure A.24 - Transition Percentages by Years in Occupation, Originated Female Dominated Occupation
CHAPTER 1: INTRODUCTION TO DISSERTATION

Background Context

In the United States, the past 50 years have seen three transformations in the structure of the labor market. The first of these is an increase in the precarity of work. Over the course of a career, an individual today is likely to work for a greater number of different employers and possibly in a greater number of occupations than 40-50 years ago. While some individuals may switch employers and occupations voluntarily, others do so as a result of layoffs and downsizing implemented by firms in the effort to stay profitable. There also has been an increase in non-standard work such as temporary, contract and part-time work which contributes to the overall precarity of the labor market.

The second transformation in the labor market is the rise in wage inequality. One defining feature of the increase in wage inequality is the widening wage gap between individuals who have at least a bachelor’s degree and those who do not. A large body of research has documented this and explored various causes including change in industrial and occupational structure, changes in technology leading to a higher demand for well educated workers and declining demand for less well educated workers, and a decline in union power to name a few.

A third change in the labor market has been the decline in gender inequality. Since 1965, women have made up a progressively higher percentage of the labor force as more women work for greater portions of their adult lives. In addition, there has been a steady decline in gender based occupational segregation as women have moved into previously male dominated
occupations. Finally there has been a narrowing of the gender wage gap although the last couple of decades have seen a leveling off of this trend.

This dissertation explores the aforementioned three trends, as well as the relationships between them through the lens of occupations and occupational mobility, or the process of an individual changing from one occupation to another. Occupations are key element of individual labor market experience; they determine the activities an individual worker engages in in each day and along with education are one of the key predictors of wage outcomes. Thus occupational structure, both the type and distribution of occupations in the labor market as well as the demographic composition of occupations is a key factor relating to wage inequality by education and gender. Furthermore, any exploration of the relationship between inequality with precarity and mobility must also consider the role of occupational mobility.

**Paper 1: Should I Stay or Should I Go? The Impact of Firm Changes, Occupational Mobility and Education on Earnings, 1965-2015**

This dissertation consists of three papers. The first paper examines the impact of inter-firm mobility on wage trajectories of three birth cohorts of young male workers (aged 18-31), focusing on how the relationship between mobility and wages has changed form 1965-2013. A key element of this analysis is exploring how occupational mobility might moderate the impact of inter-firm mobility on wages. A second element of this analysis examines how educational attainment moderates the impact of inter-firm mobility on wages and how this may have changed over time, concurrent with rising wage returns to education.

The key findings from this first paper include the following:

- The negative impact of displacement on wages is restricted to individuals changing occupations.
• The negative impact of displacement has increased over time.

• For the middle recent cohorts, firm and occupational tenure explain a substantial portion of the loss in wages due to displacement and firing. This is somewhat less true for the recent cohort.

• There is a large education differential in the impact of voluntary firm mobility on wages and this has increased over time.

• For the middle and recent cohorts, those without a bachelor’s degree do not generally benefit from voluntary firm mobility and there has been minimal change over time.
  
  o They find ‘higher wage quality’ positions, but the loss of firm and/or occupational tenure cancels out the wage benefits.

• Individuals without a bachelor’s degree who will voluntarily change firm and occupation tend to be those with worse earning prospects to begin with.

• Finding a new occupation with similar skills mitigates the wage loss due to displacement and firing and brings substantial benefits when the inter-firm mobility is voluntary.

The prevailing wisdom in Sociology, based on the seminal work by Bernhardt et al in the late 1990s has been that the impact of mobility on wages has gotten worse over time, particularly for those with less education. This research counters that argument, showing that while the impact of involuntary job loss has worsened over time, the wage benefits of voluntary inter-firm mobility have remained constant for those without a bachelor’s degree and have markedly increases for those with a bachelor’s degree or more.

Paper 2: Should She Go or Should He? Gender Differences in the Impact of Firm Changes, Occupational Mobility and Education on Earnings across the Life Course, 1965-2015

The second paper also examines the relationship between inter-firm mobility and wages and the extent to which occupational mobility and educational attainment might moderate this impact. The second paper takes a life course perspective, examining a single cohort of men and women from ages 18-55, over the years 1979-2012. This paper explores the extent to which the
relationships between inter-firm mobility, occupational mobility, education and wages vary over the life course, as a function of the duration of time since the mobility event and between men and women. This paper also explores the extent to which gender differences are due to the behavior and treatment of individual women and men as well as opposed to their occupational location in the labor market.

The key findings from the second dissertation paper include the following:

- The impact of most types of inter-firm mobility worsen with increasing age at which the mobility occurs: positive wage gains abate and wage losses are larger.

- The moderating effect of occupational mobility on the relationship between inter-firm mobility and wages varies depending on the age at which the mobility occurs:
  - For individuals without a bachelor’s degree, for mobility events that occur before the age of 30, voluntary inter-firm mobility with an occupation change ultimately brings higher wage returns than voluntary inter-firm mobility while remaining in the same occupation.
  - For individuals without a bachelor’s degree, for mobility events that occur after the age of 30, voluntary inter-firm mobility with an occupation change results in a wage loss, while voluntary inter-firm mobility while remaining in the same occupation results in no net wage change.

- For individuals without a bachelor’s degree, the wage loss due to voluntary inter-firm mobility with an occupation change that occurs after age 30 is largely due to loss of firm and occupational tenure.

- The wage gains for voluntary inter-firm mobility with an occupation change are not fully realized until three years after the inter-firm mobility event.

- Men receive a bachelor’s degree premium in the wage returns to voluntary inter-firm mobility. Women do not receive the bachelor’s degree premium for most types of voluntary inter-firm mobility.

- The differences between men and women in the bachelor’s degree premium for voluntary inter-firm mobility can be largely explained by occupational segregation.

- Wage losses due to displacement are restricted to displacement that also involves an occupation change.
• For individuals without a bachelor’s degree, when displacement with a new occupation occurs after age 30, wage losses are worse for men than for women.

The prevailing wisdom in Sociology and Economics is that voluntary inter-firm mobility is associated with wage gains, although significant gains may be restricted to mobility early in the career. Findings from this paper suggest that for less well educated workers, inter-firm mobility after age 30 that also involves an occupation change actually results in workers earning less on average over time than they might have otherwise. This highlights the variation between different types of volunteer inter-firm mobility and the importance of considering concurrent occupation changes as well as education level. A second contribution of this paper is to highlight the importance of occupational segregation in explaining gender differences in the relationship between inter-firm mobility and wages. While the literature suggests that a variety of factors contribute to the gender wage gap in general, differences between men and women in terms of the wage benefits to voluntary inter-firm mobility are almost completely explained by occupational segregation.

**Paper 3: Has the Revolving Door Shut?: Women’s Occupational Mobility and Occupational Segregation, 1965-2015**

The third paper examines the extent to which mobility by women between occupations with different levels of female representation have changed over time since 1965. The paper explores transitions between ‘male dominated’, ‘female dominated’ and ‘integrated’ occupations as well as transitions between occupations of any degree of gender representation to other occupations with a varying greater or lesser degrees of gender representation than the first. The paper uses 4 birth cohorts of women, with a range of birth years from 1923-1984, analyzing data from 1965-2013. The paper analyzes the extent to which the probability of the various transitions
mentioned above have changed during that time period as well as the extent to which the relationship between education level and the probability of specific transitions has changed over time. In addition, the paper explores the relationship between macro-economic conditions and the likelihood of these transitions.

The key findings from the third dissertation paper include the following:

- The two-year probability of changing occupations declined markedly for women between 1970-2010.

- The largest declines are in the two-year probability of transitioning out of the set of male dominated occupations, to both female dominated occupations as well as integrated occupations (net of changes in relative size of the occupational categories).

  - However, in 2010, women are still more likely to transition out of the set of male dominated occupations than out of the set of female dominated occupations.

- Overall, the two year-probability of transitioning out of female dominated occupations does not change over time. However, net of changes in relative size of the occupational categories, the two-year probability of transitioning from female dominated to integrated occupations gets substantially smaller over time.

- Once changes in relative size of the occupational categories are accounted for, the declines in transition probabilities of exiting male and female dominated occupations are driven primarily by the fact that women are much less likely to change occupations by 2010.

- A higher proportion of gender-integrated occupations is associated with more occupational mobility for women both into, out of and within gender integrated occupations.

- Whereas the two-year probability of transitioning from male dominated to female dominated occupations declines for women with a high school diploma, it actually increases for women with no high school diploma or a bachelor’s degree.

- The changing patterns over time for different educational groups actually result in a convergence across educational groups by 2010 in most two-year transition probabilities.

- Across years, women with bachelor’s degree consistently have the lowest probability of transitioning into the set of male dominated occupations.
• A higher unemployment rate is associated with a higher probability of women leaving male dominated occupations but does not appear to impact the probability of entering male dominated occupations.

The conventional wisdom in Sociology, based on the seminal work by Jacobs in the early 1980s suggests that there is considerable movement by women between male dominated, female dominated and integrated occupations and that this mobility does not decline with age. The findings from this paper show considerable declines in the degree of mobility between male dominated, female dominated and integrated occupations both over the life course of individual women and in across all women over the past 50 years.

**Overall Themes Linking the Three Papers**

*Occupation Specific Human Capital*

The first theme that arises from these papers is the importance of occupation specific human capital. Occupation specific human capital refers to the knowledge and skills that individuals develop over time while working in an occupation that allow them to be successful in that occupation. This knowledge and these skills are particularly helpful for the specific occupation although they may be transferable to other specific occupations. We see the role of human capital in the second paper, where individuals who change firm and occupation see their wages improve over the first three years in the new occupation, as they develop human capital specific to the new occupation. We also see the importance of occupation specific human capital in the finding in the first paper that individuals who move to a new occupation where the skill requirements are similar to their old occupation have markedly better wage outcomes. Finally the fact that loss of occupation tenure when changing occupations is associated with a wage loss in both of the first two papers is an indirect example of the wage benefits of occupation specific
skills. Occupational tenure is associated with a wage premium precisely because of the occupation specific human capital that long-time workers in an occupation have developed over time.

*Lack of Benefits from Job Mobility among Less Well Educated Workers*

A second theme among the first two papers in this dissertation is that workers without a bachelor’s degree generally do not benefit much from inter-firm mobility. The first paper shows that for mobility that occurs under before age 32, the wage gains are less than 5% and have only scattered statistical significance. The second paper indicates that while there are eventual gains for mobility that occurs before age 30, particularly for those who change occupations, mobility that occurs after age 30 with an occupation change results in these workers eventually having lower wages than they would have had they remained in their original occupation and firm. In addition, findings from the first paper indicate that these workers are individuals who have characteristics that are associated with lower earning prospects overall, regardless of whether experience inter-firm mobility or not.

Taken together, these findings suggest that less well educated workers are pursuing job mobility that is not particularly effective for them in terms of wages. This mobility may be based on unfounded hopes of higher wages in the new position that do not ultimately occur. This mobility also may not be entirely voluntary. For instance, given that these may be individuals with poor labor market adjustment, they may quit positions because they are frustrated by lack of advancement or have difficulty getting along with a supervisor. While these changes are not technically the result of involuntary job loss, the workers may not have a sufficient number of other job options to choose from in order to secure wage gains.
Overall, the findings suggests that it is appropriate to take a closer look at the experience of ‘voluntary’ inter-firm mobility for less well educated workers. What prompts their decisions to move job and/or occupation? Is their variation among this group in terms of their earning prospects following inter-firm mobility and what individual and labor market characteristics might account for these differences.

**Occupational Segregation among Highly Educated Women**

A final theme from the second and third papers is the somewhat surprising outcomes for highly educated women (those with a bachelor’s degree). Over the past 50 years, most of the decline in occupational segregation has been in positions requiring at least a bachelor’s degree. Thus in a general sense, declines in labor market gender inequality have been stronger among college educated women compared to women who do not have a bachelor’s degree. However, several of the findings from this dissertation suggest that women with a bachelor’s face more gender inequality than less well educated women. Results from the second paper indicate that there are not gender differences in the impact of voluntary inter-firm mobility on wages for men and women without a college degree. The gender gap is restricted to men and women who have at least a bachelor’s degree and is almost completely a function of occupational segregation, in spite of the fact that occupational segregation is lower among college educated men and women.

The third dissertation paper shows that women with a bachelor’s degree are among the least likely to transition into a male dominated occupation and among the most likely to transition into a female dominated occupation, although differences among different education levels have converged over time. The probability of transitioning from a male dominated to a female dominated occupation has also increased over time for women with a bachelor’s degree.
The findings of the second and third paper suggest that further attention should be paid to the characteristics of and factors that lead to continued occupational segregation among college educated women. Are the occupations that remain male dominated particularly unwelcoming to this set of women and if so, why is that the case? What role might college majors and socialization play in this process?
CHAPTER 2: SHOULD I STAY OR SHOULD I GO? THE IMPACT OF FIRM CHANGES, OCCUPATIONAL MOBILITY AND EDUCATION ON EARNINGS, 1965-2015

Introduction

Over the past 40 years, the structure of the United States labor market has fundamentally changed. Whereas relations between companies and employees were once characterized by long term stable relationships, the current relations are more precarious and tenuous. The use of permanent layoffs by firms as a strategy to cut costs and remain profitable has increased and the average time that employees work for a specific firm (firm tenure) has declined. There has also been a rise in contingent labor relations such as part-time, temporary and contract work (Kalleberg 2011, Farber 2008, Uchitelle 2007). In addition, the past 40 years have seen a rise in wage inequality, in particular the wage gap has widened between those who do and do not have a college degree (Cheesman-Day and Newburger 2002).

Due to these changes in the labor market, in particularly the increase in mobility of workers between firms, social science researchers have paid considerable attention to the impact that inter-firm mobility has on individual workers subsequent wage trajectories. Do workers who change firms subsequently fare better or worse in terms of their wages relative to similar workers who stay with a single firm? Research has focused both on the impact of involuntary job loss and voluntary firm switches on worker’s wage outcomes. However, in spite of the wealth of research on inter-firm mobility and wages and the knowledge of macro-economic and labor market
changes over the past 40 years, there has been surprisingly little attention paid to specifically how the relationship between inter-firm mobility and wages may have changed during this time.

Occupations are key element of individual labor market experience; they determine the activities an individual worker engages in in each day and along with education are one of the key predictors of wage outcomes. Due to the fact that over time individuals develop occupation specific skills, occupational tenure has not surprisingly been found to be a strong predictor of individual wage growth. Clearly a firm switch that is made while retaining the same occupation will be an entirely different experience from a firm change that also involves a change in occupation. It is reasonable to expect that these two types of mobility might have different impacts on the subsequent average wages. However, research on the impact of individual inter-firm mobility on wages has largely ignore the question of how the relationship between mobility and wages might be moderated based on whether or not the individual also changes occupations concurrently with switching firms.

This paper thus focuses on two areas, first how the impact of inter-firm mobility on wages has changed over the past 40 years and second, how this impact is moderated by the presence or absence of simultaneous occupational mobility. I also explore how the aforementioned patterns vary according to educational attainment. Finally I examine the extent to which the role of occupational mobility varies depending on the transferability of skills between an individuals’ initial and subsequent occupations.

Literature Review

*Inter-Firm Mobility: Theory*

Job search theory suggests that individuals seeking to find employment at a new firm are primarily motivated by a ‘rational’ desire to maximize the utility that their job allows them to
achieve. They will thus only voluntarily accept a position at a new firm if the new position provides them greater utility than their current position. In principle, utility is defined broadly and may include wages, other monetary benefits (e.g. health insurance) and non-monetary benefits such as flexibility of work. In fact, as the primary purpose of work for most individuals is to earn a living, most research on inter-firm mobility is based on the assumption that voluntary decision to change firms result from an individual’s desire to maximize wages. (Longhi and Taylor 2013, Burdett (1978) and Jovanovic (1979). Thus the job search model posits that voluntary inter-firm mobility will result in higher wages. This expectation is mitigated however by what is referred to as the ‘problem of imperfect information’ (Borjas 2005). Individuals who change firms know their starting wage at the new firm, but may be somewhat limited in their ability to project what their wages will be several years in the future relative to they might have earned if they stayed at their former position.

In addition, when an individual must change firms involuntarily, due to having lost or their previous position and being unemployed, the job search model takes a somewhat different form. While the individual may still choose to maximize their wages, the wage to which they compare the prospective position to is no longer the wages of their previous job. If they are currently unemployed and earning no wages, they may potentially be willing to accept a position paying significantly less than their former one (Longhi and Taylor 2013). Furthermore, from an institutional perspective, when firm makes the decision to displace workers in order to cut costs and remain profitable, this may indicate that the firm was paying workers more than their ‘market value’, that is what they would expect to earn on average at a similar position in the same industry (Uchitelle 2007). This when the decision to change firms is involuntary, we would expect that workers are likely to earn less at their new position than their former one.
Inter-Firm Mobility: Results

National and regional studies on worker displacement, e.g. job loss due to permanent layoffs and plant closures, since the 1970s, have overwhelmingly found job displacement results in wage declines; estimates range from 6-25%, which persist for at least 7 years (Farber 2003, Kletzer and Farlie 2003, Fallick 1996, Jacobson Lalone and Sullivan 1993, Couch and Placzek 2010) and for as long as 20 years (Von Wachter, Song and Manchester 2009).

In addition, a variety of research that distinguishes between voluntary and involuntary firm separations, based on data from 1966-2002, has shown that involuntary separations, whether being fired, laid off, or working at a plant that subsequently closed, result in lower wages at the following job relative to remaining at the same firm. On the other hand, voluntary separations, e.g. ‘quits’ have a positive impact on subsequent wages. This research includes studies focusing on specific birth cohorts (e.g. groups of individuals who were born during a specified time interval), including cohorts born 1907-20 (Mincer and Jovanovic, 1981; Black 1980), 1942-52 (Antel, 1983; Blau and Kahn, 1981a, 1981b; Bartel and Borjas, 1981), and 1958-65 (Keith and McWilliams 1995, Perticara, 2002; Fuller, 2008). Other than for the earliest cohort mentioned above, who were analyzed in mid-life, cohort based studies have focused on the first 10-20 years of the respondents professional lives. Other research has been based on samples of the entire workforce (e.g. all working ages), including data from the mid-1970s to the early 1990s (Polsky, 1999, Ruhm, 1997, Moore, 1998). While most of the research has focused on men, the studies by Keith and McWilliams (1995), Fuller (2008), Blau and Kahn (1981a, 1981b) also included women1.

1 Ruhm (1997) and Moore (1998) used all heads of household who were predominantly men.
Individuals with higher education have more resources in the labor market, given that there are a greater set of positions for which they qualify. Therefore we might expect that with increasing educational attainment, the wage gains following voluntary firm switches would be stronger and wage losses following job loss would be ameliorated. It is also possible that since individuals with higher education tend to earn more, they may suffer worse wage losses following displacement in that they ‘have further to fall’. In fact, research on the relationship between educational attainment and the impact of involuntary job loss has not produced consistent results, with some research suggesting that education provided a protective effect vis a vis wages following job loss and other research indicating the opposite result (Koeber and Wright 2001, Stevens 1997, Helwig 2001). There is a dearth of research on how voluntary inter-firm mobility might be moderated my educational attainment, which is why I will address this topic in this dissertation paper².

An issue in the literature discussed above is that firm switches are potentially endogenous. That is, individuals who change firms voluntarily may be workers with characteristics that would enable them to earn high wages regardless of their firm location; the converse may be true of those experiencing involuntary job loss. While Bartel and Borjas (1981), Antel (1983), Blau and Kahn (1981a, 1981b) and Perticara (2002) use methods to address the endogeneity issue (e.g. Heckman models or fixed effects), the other authors do not. Furthermore the Bartel and Borjas (1981), Antel (1983), and Blau and Kahn (1981a, 1981b) articles all analyze data from 1969-1972. Therefore only one article (Perticara 2002) using data

² Kronberg (2014) includes models for stratified by educational attainment when examining the impact of involuntary and voluntary firm switches on wages. However shed does not explicitly make comparisons across models and the models are too complex for the reader to do this. There is also one article in the Monthly Labor Review (2005) which suggests that men with at least some college benefit more from voluntary mobility than men with no more than a high school education but no statistical significance is tested and it does not appear that any other variables are controlled for.
from other time periods addresses endogeneity. This is more potentially problematic for the results on voluntary firm separations. For the involuntary separations, many authors restrict the findings to job displacement, which is relatively exogenous vis a vis worker characteristics, or analyze job displacement and firing separately.

**Inter-Firm Mobility: Changes over Time**

While the literature discussed above includes data from multiple cohorts, little research has been done on the impact of firm mobility for more recent entrants to the labor market: those born 1980 or later, who are often referred to as the millennial cohort. Furthermore, no research that distinguishes between voluntary and involuntary job loss has compared results across birth cohorts. This an important issue to consider because the various cohorts entering the labor market from the 1960s through the present have joined and worked within very different labor markets and under different economic conditions.

Over the past 40 years, the structure of the United States labor market has been transformed. Labor relations from 1945-1975 were characterized by what has been referred to as the ‘post-war accord’. Relationships between employers and labor tended to be stable and long-term, and especially in the manufacturing industries, union presence was strong. Workers frequently remained at a single company for a long period of time and were rewarded by on the job training, promotions and wages which rose with seniority, three investments by firms in their workers which together are referred to as the ‘internal labor market’. When faced with financial difficulties, employers tended to use layoffs as a last resort strategy. To a certain extent the aforementioned labor market context represents an ‘ideal type’, which applied in particular to the labor market opportunities available to white men. Nevertheless, in terms of the overall stability
of employer-employee relations, the labor market context from 1945-1975 was markedly different than that of the present day for significant proportion of the workforce.

Several macro-economic changes in the 1970s lead to the dismantling of the ‘post-war accord’ between capital and labor. Increased competition from European and Japanese firms and a larger corporate emphasis on accountability to stockholders forced American firms to be much more concerned about the ‘cost’ of labor. At the same time, advances in technology and communications allowed for the outsourcing of jobs to cheaper labor in overseas factories (Kalleberg 2010). This combination of forces lead to several changes in the institutional relations of labor market including a rise in contingent work, an increase in layoffs, and a decline in worker tenure as well as the wage returns to tenure. While the post-war accord began to be dismantled 40 years ago, there have also been significant changes in the labor market within this time period. For instance, in the 1980s, most layoffs were in the manufacturing industries since the mid-1990s, displacement has spread to include financial and service industries as well. In addition, the level of labor demand has cycled throughout this time period with unemployment spikes in the early 1980s and in 2008-2010.

These various changes in economic conditions and labor market context have likely contributed to the wage trajectories of cohorts of individuals entering the labor force at different time points (Bachman et al 2009). There is a general trend that wage trajectories for men have stagnated or declined since the 1970s; this is particularly true for men without a college degree. Bernhardt et al (2001) compared the wage trajectories through age 36 of men born between 1942-52 with those born from 1958-1965 and found for individuals with less than a bachelor’s degree, the wages of the later cohort were consistently less than the wages of the earlier cohort; differences which widened as the cohorts aged. For individuals with a bachelor’s degree, the
wages of the more recent cohort were also lower, although the differences were much smaller and did not increase consistently with age. In addition, Beaudry et al (2014) examined wage trajectories for college educated workers aged 25-30 between 1990 and 2010 and found that these became progressively flatter after 2000.

Given the aforementioned changes in the structure of the labor market and earnings trajectories, we might also expect that there would be variation in the impact of firm mobility on wages during this time. However, there has been little attention to this issue. The one seminal work on this topic, by Bernhardt et al (2001), is problematic because the analysis does not differentiate between involuntary and voluntary job loss\(^3\). Bernhardt et al (2001) find that for men with a no more than a high school diploma, the impact of firm mobility on wages are negative for men born 1958-1965, but positive for men born 1942-52. However, these findings may potentially be entirely explained by the fact that a (much) higher percentage of firm mobility for the later cohort resulted from involuntary job losses. For men with at least some college, who are much less likely to suffer involuntary job loss (Boisjoly, Duncan and Smeeding 1992), the impact of firm mobility is positive for both cohorts.

**Occupational Mobility: Theory**

Since Blau and Duncan’s seminal work (1967), sociologists have had a strong interest in occupational mobility, that is the movement between lower paying and higher paying occupations (and vice versa), whether across generations or over the life course. Theory suggests multiple contradictory effects. The job search theory and the problem of imperfect information discussed earlier also apply to voluntary decisions to change occupations. Along these lines,

\(^3\) They also did not use any methods to deal with endogeneity.
Leigh (1976), and Janovic (1997) proposed that individuals use their education, training and skills developed on the job and (attempt to) move through a series of progressively more well paying occupations over their working life. However, an alternate theory suggests that staying within one occupation is associated with greater wage gains. This draws upon the notion that spending significant time in one occupation allows for the development of occupation specific skills which make the employee more valuable and result in higher wages. Spilerman (1977) compares what he refers to as craft or professional career lines, where individuals remain within one occupation, earning progressively higher wages due to acquiring occupation specific skills, with a chaotic career line which is characterized by frequent movement between occupations and stagnant wages.

**Occupational Mobility: Results**

Most sociological research on occupational mobility has focused on the extent to which individuals have the opportunity to move between large groups of occupations (e.g. professional, clerical, laborer), which are in a sense proxies for detailed social classes. Income mobility here is implied (e.g. doctors earn more than crane operators), but it not directly measured (Haller 1975, Holmes and Tholen 2013). Recent research in this vein has also analyzed more detailed occupational categories. For instance, Kambourov and Manovskii (2008) found that from 1968-1997, two year occupational mobility has increased from 10-15% at the one digit occupational level and from 16-20% at the three digit occupational level.

Researchers have also focused on the characteristics that are likely to lead to occupational mobility. Several papers have found that age, being older, male, more highly educated and better paid leads to lower likelihood of switching between both 1 digit and 3 digit occupations (Parado,
Occupational mobility is more likely for blue collar occupations (various forms of operator and laborers) although movement tends to be between various blue collar occupations Kim, 2013; Spilerman 1977).

A small body of literature within sociology and economics has also looked at the impact of occupational mobility on subsequent wages. The results are somewhat inconclusive. A few studies using data from the 1960s through the 2000s have found positive associations between occupational change and subsequent wages using one digit and three digit occupational categories (Parado, Caner and Wolff, 2007, Leigh 1976). However, using three digit occupational categories Gius (2014) found that while occupation changes within an industry were associated with higher wages, occupational changes that also involved an industry shift were associated with lower wages. Furthermore, Hollister (2012) found that during an individual’s first 10 years of work experience, change between 1 digit occupational categories when moving firms was associated with a greater likelihood of both an increase and a decrease in wages during experience, relative to staying at the same firm in the same occupation. Finally, Even and Macpherson (2003) found that changing three digit occupation and industry together had a positive impact on workers earning the minimum wage, but no impact on workers earning above the minimum wage, and Gardeksi and Neumark (1998) found that there was no impact of occupational change in the first 5 years of work experience on wages.

Part of the inconsistency of the aforementioned research findings likely stems from the fact that none of the studies separate voluntary and involuntary occupational switches, that is, whether or not the occupational change was concurrent with an involuntary job loss. In fact the

---

4 This likely uses 3 digit occupations although I couldn’t find it specified in the paper.
Hollister (2012) and Gardekci and Neumark (1998) are the only papers which refer to firms at all. It is reasonable to expect that, like with firms, voluntary occupation switches might lead to higher wages while involuntary occupational changes would be associated with lower wages. When the two experiences are combined, the results may be unstable from paper to paper and are difficult to interpret regardless. In addition, only the Parrado, Caner and Wolff, 2007 and Gardecki and Neumark (1998) papers use methods (instrumental variable generalized least squares and fixed effects) to address any potential endogeneity of occupational switches. Those who switch occupations may be particularly innovative and would have had high wages regardless. On the other hand, occupational switchers may also be unstable and would have had lower wages even if they did not switch occupations. Although the direction of the endogeneity is uncertain, it is important to address it in some fashion.

Two articles also specifically examine the impact of occupational switching for displaced workers. Both Choi (1996) and Kambourov and Manovskii (2009) found that remaining in the same occupation after being displaced serves as a protective factor. The wage losses for displaced workers who remained in the same occupation (6% wage loss) were significantly less than those for displaced workers who changed occupation (18% wage loss) Kambourov and Manovskii (2009). Choi (1996) also found that the protective quality of retaining one’s occupation following job displacement was stronger as education increased. This is interesting as research has indicated that educational level is not associated with the level of earnings loss following displacement in general in any consistent fashion (Koeber and Wright 2001, Stevens 1997, Helwig 2001).

A related body of literature, primarily in economics, has examined the impact of occupational tenure on wages. In particular, researchers have compared the impact of
occupational tenure to industry and firm tenure, with findings that occupational tenure is by far
the most important Kambourov and Manovskii (2009), Yamaguichi (2010), Pavan (2011).
Returns to occupational and firm tenure vary by education as well as occupation. For instance,
Sullivan (2010) found that returns to occupational tenure were much larger for professional craft
and service occupations as compared to clerical, labor and operative occupations. Yamaguichi
(2010) found that over the first 10 years of labor market experience, for those with a high school
diploma, career tenure (defined by years in the same occupation and industry) accounted for a
13% increase in wages while employer tenure only accounted for a 5% increase in wages. For
individuals with a bachelor’s degree, the difference was even larger; career tenure accounts for
18% increase in wages while employer tenure accounted for < 1%.

A final body of literature on occupational mobility operationalizes occupations in terms
of the skills used in that occupation. These studies take two forms. In the first type of research,
skill based categories are created by conducting factor analysis based on the knowledge and
skills used in the occupation. Then the impact of switching these skill clusters on wages is
compared to the impact of switching standard 1 and 3 digit occupational categories. Using
German data, Geel and Backes-Gelner (2011) found that the impact of changing skill cluster was
negative relative to staying in the same occupation, but changing occupation and remaining in
the same skill cluster had a positive impact on wages. However Poletaev and Robinson (2008)
found that following a job loss, staying within a 3 digit occupation resulted in a smaller wage
loss than remaining within a skill cluster. A second set of studies also use a variety of methods
to calculate indices of the difference between occupations before and after a switch based on the
extent to which they share activities and skills. Not surprisingly, the further the occupations are
from each other in terms of skill sets, the worse the wage outcomes (Gathman and Schonberg 2010, Ormiston 2014).

Summary on Inter-Firm and Occupational Mobility

What we know:

- Involuntary firm mobility tends to lead to wage losses; voluntary firm mobility tends to lead to wage gains.
- Remaining in the same occupation appears to ameliorate the wage losses from involuntary job loss.
- Occupational tenure and firm tenure lead to wage gains but occupational tenure leads to larger wages gains.
- While education does not appear to moderate the impact of involuntary job loss in general, it may strengthen the protective nature of retaining one’s occupation following involuntary job loss.
- The more closely related the skills are between a current and former occupation, the better the wage outcomes.

What we do not know:

- How incorporating occupational change (or lack thereof) may change the impact of firm mobility on wages.
- When firm mobility is voluntary, whether occupational mobility or retaining one’s occupation leads to better wage outcomes
- How the impact of all forms of firm and occupational mobility vary over time in the last 50 years.
- The extent to which the impact of voluntary firm mobility and voluntary occupational mobility vary by educational level.
Research Questions

This paper will focus on the following research questions:

- What are the impacts on wages of?
  - voluntary inter-firm mobility while remaining in the same occupation
  - voluntary inter-firm mobility while changing occupations
  - involuntary inter-firm mobility while remaining in the same occupation,
  - involuntary inter-firm mobility while changing occupations

- How do the above findings vary by educational attainment?

- How do the above findings vary over time from 1965-2015?

- To what extent is the impact of inter-firm and occupational mobility a function of the degree to which the prior and new occupation use similar skills?

Figure 2.1 presents a diagram of the conceptual model for my analysis.

Data and Methods

Sample

One of the primary research questions of this paper is how the impact of inter-firm and occupational mobility on wages has changed over the past 50 years. In order to assess changes over time, I use the strategy employed by Bernhardt et al (2001). I use data on three cohorts of workers who born and thus entered the labor market at distinct time points. I then follow the employment trajectories of these three cohorts at identical ages (and thus different points in chronological time). By comparing patterns across these cohorts I assess how the impact of mobility on wages varies over time.

In this paper, I examine the experiences of three cohorts of workers, those born 1942-52, 1957-64 and 1980-84. Each of these three cohorts has entered the labor market under different...

---

5 How these patterns vary by age will be addressed in the next paper.
economic conditions. The original cohort entered the labor market (1960-70) when the internal labor market was still strong, long-term employment with a single firm was still common and layoffs were rare. The middle cohort entered the labor market (1975-82) just as the labor market was becoming more precarious, with increases in layoffs and a decline in employer tenure. This was also a period of extremely high unemployment. The recent cohort entered the labor market (1998-2002) after the aforementioned changes in the employer-employee relationship had been solidified. However, they also entered the labor market in a period of relative prosperity, although by their late 20s, this was no longer the case (Kalleberg 2010). In addition to influencing the wage trajectories of these three cohorts (Bachman 2009), it is also likely that these various economic conditions have impacted the relationship between various types of inter-firm mobility and wage outcomes.

For each cohort I include a sample of men aged 18-31. Thus I examine the impact of mobility within the context of the early years of work. This is in part determined by the fact that data is only available for the most recent cohort through age 31. However, young workers (those in their teens and 20s) have been the focus of considerable attention by labor market scholars. It is in these years that individuals complete their education, enter the world of work, and explore and frequently decide on occupations. Decisions made during this age period will set trajectories that impact their earning power for the remainder of their lives (Rindfuss, Swicegood and Rosenfeld 1987). A substantial portion of the occupational and firm mobility that occurs in the

---

6 The national unemployment rate ranged from 3.5-6.7 between 1960-70. However it was <= 5.7 in every year except 1961. The national unemployment rate ranged between 5.8-9.7 from 1975-82 and was above 7.0 in all but two of those years. The national unemployment rate ranged from 4.0-5.8 from 1988-2002.

7 While data for the original cohort are technically available through age 39, due to both sampling structure and attrition, the sample size gets much smaller after age 31. For instance while there are nearly 3000 cases for each year of age in the mid-20s, there are fewer than 750 respondents for each age from age 35 on.
working years is likely to occur during these ages. In addition, approximately two thirds of lifetime wage growth occurs in the 20s and early 30s (Bernhardt et al 2001).

I restrict the sample to men for two reasons. First, much of the research on inter-firm mobility, particularly cohort specific analyses, have used samples of men. Therefore, in order to best compare my results to previous findings I restrict the sample to men. Second, in the time period examined (1965-2015), women’s labor market experiences varied dramatically from men as women entered the labor force in much greater numbers and made inroads into previously male dominated occupations. Thus the changing labor market contexts (e.g. increased precarity) over the past 50 years have impacted women differently from men. Thus it is appropriate for analysis of women to be done in a separate paper. In the third paper, I focus on comparing cohorts of women (although using a different outcome).

The data are from the National Longitudinal Surveys for three cohorts: NLS Young Men (5225 men born 1942-52; original cohort), NLSY79 (8979 men born 1957-64; middle cohort), and NLSY97 (4599 men born 1980-84; recent cohort). These nationally representative surveys have been widely used in the social sciences to examine labor market outcomes. In addition, they provide the most extensive data available for comparing patterns across cohorts. As mentioned, I will use samples of men aged 18-31. Men aged 18-22 who are enrolled in school will be excluded. This is because firm and occupational mobility for individuals still completing their schooling does not reflect true career patterns, as schooling rather than work is likely the focus of their energy at the time. In fact the Department of Labor does not consider full time students to be ‘employed’ even when they hold jobs.

---

8 I exclude the military sample (numbers not included in those presented).

Attrition in the NLSY79 is low. For the NLSY79, in the years 1979-93, the response rate for living respondents was at least 90% in all years through 1994. For the NLSY97, retention rates are somewhat lower, ranging between 80-93% over the course of the survey, with retention rates over 90% through the fourth round (2000). For the NLS Young Men, retention rates are still a bit lower; response rates for living respondents through age 30 are 72%-80%, for 1969-81 (they higher before 1969), although response rates are at least 76% in all but one year. Bernhardt et al (2001) who conducted a similar analysis (impact of firm mobility on wages) using data from the NLSY79 and NLS Young Men ages 16-37) did an extensive examination of attrition in the NLS Young Men, comparing the characteristics and regression coefficients of the remaining sample and those lost to attrition (using the years those respondents were present). The determined that attrition had minimal impact on their findings.

Variables

The outcome variable is the natural log of the hourly wage rate, for all individuals who have wages in the past year. All wages are adjusted using the Consumer Price Index (CPI). I use standard controls used in models with wage outcomes including calendar year, education (no high school diploma, high school diploma, some college, bachelor’s degree or higher),
race/ethnicity (white, black, Latino, multiracial, other\textsuperscript{9}), lifetime weeks of work experience, occupation (1 digit categories), industry (1 digit categories), firm tenure (years), lifetime occupation tenure (years), marital status. Occupation and industry will capture if individuals in some occupations/industries (which may be higher or lower paying) are more likely to change firm and/or occupation voluntarily or not.

I do not include a variable for age. This is because as I am using a cohort sample, age and calendar year are highly collinear. I chose to use calendar year rather than age after exploratory data analysis suggested that the patterns of wage trajectories over time were more accurately modeled by year, rather than age. While age captures elements of the relationship between life course and wages, calendar year is most appropriate for capturing the effect of changing macro-economic conditions. For each cohort, I use a functional form for calendar year that both best fit the data and represents what we know about macro-economic conditions in that time period. For the NLS Young Men, I model calendar year as both a linear an squared term. This represents that real wages increased up until about the mid-1970s and declined slightly afterwards. For the NLEY79, I use a linear term for calendar year as real wages tended to increase slightly from the mid-1980s (recovery from the early 1980s recession) through the mid 1990s. For the NLSY97, I use a linear term combined with a dummy variable to let wages be flat from 2000 2008 and decrease from 2008 (as a result of the recent financial crisis).

The key variable of interest is type of inter-firm mobility. I measure this by a seven category variable: 1) remained in same firm, 2) changed firm voluntarily and remained in same occupation, 3) changed firm voluntarily and changed occupation, 4) displacement from previous

\textsuperscript{9} The NLSY does not collect information on whether a respondent is Asian American or Native American specifically. Multiracial is only available in the NLSY 97. Other is only available in NLSY Young Men. Asian American and Native American appear to be lumped with white in NLSY79 and NLSY97.
fired from previous firm and remained in same occupation at subsequent position 5) displacement from previous firm and changed occupation at subsequent position 6) fired from previous firm and remained in same occupation at subsequent position 7) fired from previous firm and changed occupation at new firm. I define a displacement as an involuntary job loss that is not related to the characteristics of the employee e.g. (layoff, plant closure, layoff, end of temporary job). It is important to distinguish these displacements from firing as being fired is generally related to the employee having poor workplace attitudes or behaviors which may impact prospects for future employment. Thus we would expect that wage losses following firing may be worse than wage losses following displacement. A voluntary firm move is one that does not involve either type of involuntary job loss\textsuperscript{10}.

The actual measure of firm-mobility consists of 6 time varying variables each measuring whether a specific type of inter-firm mobility has occurred at least once before the survey year, e.g. one variable for voluntary firm switches with occupation change, another for voluntary firm switches while staying in the same occupation, etc. Because this measure is cumulative, it allows for effects that persist over time. A variant of this method has been widely used in the literature on firm changes (Fuller 2008, Keith and McWilliams 1995, Bernhardt et al 2001 (one chapter), Gardecki and Neumark 1998, Light and McGarry 1998)\textsuperscript{11}. Some of the aforementioned articles

\textsuperscript{10} Another type of mobility is mobility due to family related reasons. As will be discussed in the next paper, while these changes are technically voluntary they may not result in higher wages. I do not distinguish them here because the NLSY Young Men survey does not separate these types of mobility from other voluntary mobility. However, the incidence of family related mobility among young men is very low as determined from the data from the NLSY79 and NLSY97 data. Thus this should not be problematic for this paper. For this paper I do not distinguish between occupational changes into managerial and non-managerial positions because the occupation categories (1960 codes) used by the NLSY Young Men survey are very problematic in terms of determining what a managerial occupation is (e.g. no codes for supervisors, several finance related positions merged with managerial jobs. For the next paper I will distinguish between managerial and non-managerial occupations.

\textsuperscript{11} I do not use an alternate method which is frequently used in the Economics literature. This method assesses whether a change has occurred in some finite period of time and for the outcome uses the change in log wages between the two time periods. This method is intuitively appealing as it allows us to isolate the impact of a specific firm change (of some specific type) on the immediate change in wages. However, this method makes unreasonable
actually measure the cumulative total number of each type of inter-firm mobility discussed. I explored using this method but decided against it given that the literature suggests that the first instance of voluntary mobility may be the most beneficial and the first instance of involuntary mobility the most detrimental (Fuller 2008, Perticarra 2002). I did experiment with including additional variables for the total number of subsequent events of each type of mobility. Likelihood ratio tests indicated that the only measure of subsequent events to significantly improve model fit is the measure of number of subsequent displacements with an occupation change and I include this variable in the models\textsuperscript{12}.

In order to assess the moderating effects of education, I include interaction terms between having a bachelor’s degree and three of the measures of inter-firm mobility: displaced with new occupation, voluntary with new occupation, voluntary, remaining in same occupation. As discussed, I distinguish bachelor’s degree holders as these individuals may have more power and choice in selecting firms and occupations due to possession of the bachelor’s degree. Therefore voluntary changes may benefit them more and involuntary changes may hurt them less. I do not include interaction terms for the other three types of inter-firm mobility as the percentage of the assumptions about the functional form of the relationship between firm and occupational changes (and the control variables) and wages that are very different from the assumptions in standard econometric models.

The problem has to do with the mathematical properties of the logarithm. In typical models, we use the natural log of wages as the outcome. In models with $\ln(\text{wage})$ as the outcome, one unit change in any independent variable results in wages being multiplied by $\exp(\beta)$. In a model with $\ln(\text{wage})_{t+1} - \ln(\text{wage})_t$ as the outcome, a one unit change in any independent variable results in the ratio of the wages being multiplied by $\exp(\beta)^{11}$. This is a very different functional form, with no specific theoretical justification. And functional form matters. Using the wrong form can result in very biased and unreliable coefficients. As just an example, the coefficient for age is positive in standard econometric models of wages, but it is negative when the difference in log wages is used as the outcome.

To put this issue in perhaps more intuitive terms, a model with log of wages as the outcome allow us to interpret (approximately) any coefficient ($\beta$) as the percentage change in wages occurring for a unit change in any independent variable. However for the model with $\ln(\text{wage})_{t+1} - \ln(\text{wage})_t$ as the outcome, for a unit change in any independent variable, we multiply ($\%$ change in wages/100) + 1) by $\exp(\beta)$. Thus, using a very loose conceptual approximation, this model is estimating something akin to the impact of a unit change in the independent variable on the ‘percentage change in the percentage change’ of wages.

\textsuperscript{12} The incidence of subsequent events for voluntary, fire and displacement while remaining in the same occupation and fire with an occupation change are very small (occurs in <= 6% of sample).
sample who has experienced these events and has a bachelor’s degree is very small (e.g. < 5%; in some cases < 1%). Therefore estimates of interaction terms would be unreliable.

Consistent with much of the literature, I do not analyze occupation changes within a single firm (Pavan 2011, Yamaguichi 2010). Such occupation changes are difficult to interpret because they may result from many factors including promotions, demotions, firm restructuring, individual choice etc. Such changes do not necessarily reflect a decision on the part of the employee to change occupations, as even occupation changes following involuntary job loss do.

Occupation is measured in 3 digit census categories. The NLSY Young Men survey uses 1960 census occupations, the NLSY79 uses 1970 census occupations and the NLSY97 uses 2000 census occupations. Based on the suggestions at my proposal defense I will use the categories provided by each survey to analyze data from that survey (e.g no harmonizing).

Finally I use variables to measure the degree of difference between the skills used in the individual’s current and former occupation. The lower the difference, the more skill transferability between the occupations. I use skill measures for the NLSY79 and NLSY97 cohorts; there was not data available which allowed for matching skills with the 1960 occupational codes used by the NLS Young Men survey.

For the NLSY79, I use Dictionary of Occupational Titles scores on 12,100 occupations aggregated (a weighted average) to Census 1970 occupation categories (using ICPSR study 07845). For occupation changers, I take absolute value of the difference between the current and former occupation on each of 18 indicators used by Yamaguchi (2010). I then take the average of the new occupation – prior occupation differences for 18 indicators to make 8 scales also used by Yamaguchi (2010). Because individuals will learn the new skills in their new occupation over time, these skill differences are applied to the first and second year in new occupation, and
coefficients on them are allowed to vary between the first and second year\textsuperscript{13}. Subsequent years and persons who have not yet changed occupations receive a score of 0 (e.g. no difference between the occupations). The skill scales are as follows:

**Skill Scales**

- General Educational Development (1-6)
- Cognitive Aptitudes (1-5)
- Worker Function related to Data (0-8)
- Worker Function related to People (0-8)
- Social Aptitudes (0-100)
- Physical Aptitudes (1-5)
- Worker Function related to Things (0-8)
- Strength (1-5)

The description of the scales is as follows: General Educational Development takes the highest score on three measures of math, reasoning and verbal ability. This measures the level of abstraction and complexity that are required for the activities of the job, in terms of activities of job e.g. reasoning – scientific thinking vs follow instructions. Cognitive Aptitudes is the average of intelligence aptitude, verbal aptitude, and math aptitude. This assesses what aptitude level is required to do job; it is a ranking compare to population at large. The three Worker Functions scales rank how complex the activities of the occupation are related to category. For instance for ‘People’, ‘take instructions’ is considered less complex than ‘mentor’. For ‘Data’, ‘copy’ is less complex than ‘analyze’. For ‘Things’, precision work is considered more complex than operating simple machinery. The Social Aptitudes scale includes the aptitude required for the occupation on the following types of activities: influencing people, directing activity, dealing with people beyond giving and taking instructions. This is measured by the percentage of persons in occupation requiring this skill. Physical aptitudes is the average of the following: motor

\textsuperscript{13} I explored using applying them to the third year also, but none were statistically significant and there was no change in the mobility coefficients so I stopped with two years.
coordination, manual dexterity, finger dexterity, color discrimination, eye-hand-foot coordination, spatial perception, form perception.

For the NLSY97, I use O*Net scores on 923 occupations aggregated (a weighted average) to Census 2002 occupation categories (which I then matched with the Census 2000 categories used in the Recent Cohort survey). For occupation changers, I take the absolute value of the difference between the current and former occupation on each of 35 indicators and average them to make 7 scales devised by O*Net. For the NLSY97, the skill difference is weighted by the importance of the skill to the occupation, which is also provided by O*Net in a 4-5 point ranking. As with the Middle Cohort, the skill differences are applied to the first and second year the individual is in the new occupation. Subsequent years and persons who have not yet changed occupation are assigned a value of 0 (no difference in skill). The scales are as follows:

Skill Scales (all are on 7 point scale):

Content (Academic)
Process (Thinking/Learning)
Social Skills
Complex Problem Solving Skills
Technical Skills
Systems Skills
Resource Management Skills

Content includes measures of reading, writing, mathematics, science skills. Process assesses critical thinking, active learning, and learning strategies, e.g. ability to monitor and assess self-performance. Social skills include persuasion, negotiation, service orientation – (does the individual want to help people), instructing, and social perceptiveness. Complex problem solving skills involve the ability to identify problems and find solutions. Technical skills include technical design, equipment selection, and equipment maintenance, e.g. determine when it is needed and perform it, installation, programming (computers), troubleshooting, monitoring of
gauges and dials, and repairing. Systems judgement includes decision making, e.g. considering the costs and benefits of acting, identifying measures of performance. Resource Management involves management of financial, material and personnel resources.

**Analysis Techniques**

The data I use are longitudinal and the unit of analysis is the person year. The form of the data is thus $Y_{it} = X_{it}\beta + \nu_i + \epsilon_{it}$ where $Y_{it}$ is log of wages at time ‘t’, $X_{it}$ is a matrix of the independent variables (including the measures of firm change) at time ‘t’, $\nu_i$ captures time invariant unobserved individual characteristics and $\epsilon_{it}$ captures time varying unobserved characteristics at time ‘t’. Due to the presence of $\nu_i$ the error term ($\nu_i + \epsilon_{it}$) is correlated over time. I will use thus use random effects models to account for this correlation and produce efficient coefficient estimates and correct standard errors. Because there may be correlation between time invariant unobserved individual characteristics that may influence both wages and the propensity to change firms or occupations voluntarily or involuntarily, I will also use fixed effects models to analyze the data. There are several ways to mathematically represent a fixed effects model, but one way to think about it is including a dummy variable for each individual in the model, which absorbs (and hence controls for) all of the unobserved time invariant individual characteristics.

If the coefficients for the random effects and fixed effects models vary (via a Hasuman test), this suggests that there is correlation between the time invariant error and (at least one of the) independent variables and so the random effects coefficients are not consistent. If this is the case, I will focus interpretation on the fixed effects models. I will use robust standard errors for
both sets of models, to adjust for any remaining heteroskedasticity and serial correlation as well as correlated errors for respondents who are from the same household\textsuperscript{14}.

One condition for the fixed effects models to be effective is that there be sufficient variance in the independent variables within individuals over time. Figure 2.1 shows the percentage of individuals who have at least one of each of the types of firm change, thus resulting in variance for that variable for that specific person. While some of the percentages are not, given the large sample sizes they appear reasonable for detecting effects.

I estimate three fixed effects models. The first model includes the variables to measure inter-firm mobility, including interaction terms, and all of the control variables except for firm and occupational tenure. The second fixed effects model includes the controls for firm and occupational tenure. I estimate separate models here because I consider firm tenure and occupational tenure to be \textit{intervening} variables. When a person changes firm and/or occupation, by definition their firm/occupational tenure clock will be reset at 0. When we control for firm and occupational tenure we are in essence estimating the effect of mobility on wages if there was no effect (likely a penalty) on wages due to loss of tenure. This is not very realistic as the loss of tenure occurs by definition. However, while they are not that useful for capturing actual effects on wages, models with tenure controls are helpful in that they let us estimate what percentage of wage loss (for instance) due to displacement is due to loss of tenure and what the impact of voluntary firm mobility would be if there was no loss of tenure. For voluntary firm mobility this

\textsuperscript{14} There is an alternate method used in some economics articles called the IVGLS estimator. This is essentially a variant of the fixed effects models that uses the average of some independent variables as instrumental variables. Like the FE estimator, the IVGLS estimator produces consistent estimates and correct standard errors. However, the IVGLS estimator is more efficient. The IVGLS estimator has also been criticized in the literature (Pavan 2011) as producing based/inconsistent estimates in practice. Due to this controversy, I choose not to use this estimator.
in essence lets us compare the ‘wage quality’ of the position itself, e.g. what would be earned at the new position if the tenure was equivalent to the old position.

The third fixed effects model does not include the tenure variables but includes the variables to measure the differences in occupational skill between the current and former occupation for occupation changers. As with tenure, skill differences can be considered intervening variables between inter-firm mobility that involves an occupation change and subsequent wages. What this fixed effects model essentially estimates what the impact of inter-firm mobility would be if the individual could enter a new occupation with exactly the same skills as their former occupation. While this is not exactly realistic, it allows us to assess the proportion of wage loss which is due to skill differences and the wage gain that could be approximated by entering an occupation with very similar skills. For models with tenure controls and/or occupational skill difference variables, I use bootstrap methods to calculate standard errors to test the significance of the difference of coefficients for the inter-firm mobility variables between the original models for each cohort and the models with tenure or skill controls.

For most variables, there is very little missing data in the sample and therefore I used listwise deletion techniques. However, for the original cohort, the survey variable to assess whether an inter-firm change is due to displacement, firing or is voluntary is missing for 8.7% of all person-year observations (and 26.6% of observations for which there should be data, e.g. an inter-firm change occurred in the person year). Therefore, for the original cohort I use multiple imputation techniques to impute values for the reason for changing a firm. The method was as follows: I used a multinomial logistic regression model with education, race, employment status, 1 digit occupation, 1 digit industry and calendar year to estimate coefficients for the various types of reasons for inter-firm mobility (displacement, fire, voluntary). Then I created predicted
probabilities of the three outcomes (displacement, fire, voluntary) for each observation with
missing data. Using these predicted probabilities as a multinomial distribution for that person, I
then took a random draw from that distribution. The outcome of that random draw
(displacement, fire, voluntary) was then assigned to that observation. I then used the imputed
outcome in conjunction with the variables for whether an occupation change had occurred to
create a variable for which type of inter-firm mobility had occurred for that observation in that
person-year. Then with the inter-firm mobility variables for the other person-year observations, I
created the cumulative measures of whether an event had ever occurred and how many
subsequent events had occurred. I repeated this process five times. I then estimated the models
for the original cohort five times and used the average of the coefficients as the final coefficients
and calculated the standard errors using the method provided by Allison (2002, p. 31)\(^\text{15}\).

In addition to what has been previously discussed, I conducted the following sensitivity
tests for my models:

- For individuals with an occupation in one of the ‘not otherwise specified categories’: If
they changed industry at the 1 digit level, I ran models including them as having changed
occupation. These model results were barely distinguishable from models where these
person-years were not included as occupation changers.

- Excluding the following calendar years from the NLSY79: 1985, 1987, 1990, 1992 and
the following years from the NLSY97: 2005, 2007, 2010, 2013. I did this because the
NLS Young Men does not have data for the following 4 years: 1972, 1974, 1977, 1979.
Therefore this analysis explored whether the cohorts are not comparable due to missing
data. The excluded years were chosen to match the originals maple as closely as possible
in terms of age (and for the middle cohort they are the same years excluded by Bernhardt
et al 2001). In this analysis, when a year was excluded I only allowed one type of inter-
firm mobility to occur in the resulting two year period, as would be the case if a survey
year was missing (e.g. if an occupation change and/or involuntary firm change occurs in

\(^{15}\) Of course the validity of multiple imputation depends on the data being missing at random. While this cannot be
specifically tested, I did compare those missing data on reasons for leaving a firm with those who changed firm but
were not missing on the reasons for doing so on several independent variables: race, education, industry, occupation,
employment status, age. The two groups were remarkably similar. For instance, using these variables the average
predicted probabilities of displacement, firing and voluntary inter-firm mobility were .24, .03, .73 for the individuals
with missing data and .25, .04 and .72 for individuals with complete data.

37
the two years it is considered an inter-firm mobility with occupation change and/or involuntary firm change). The results are very similar to the original models and can be made available to journal reviewers on request.

Results

Throughout the presentation of the results I refer to the NLS Young Men as the ‘original cohort’, the NLSY79 as the ‘middle cohort’ and the NLSY97 as the ‘recent cohort’.

Descriptive Statistics

Figure 2.2 shows the percentage of respondents who experienced the various types of inter-firm mobility at least once by age 31. We see that the incidence of changing firms with an occupation change either voluntarily or involuntarily has tended to increase over time, although the peak for displacement with an occupation change occurs for the middle cohort. However, displacement and voluntary inter-firm mobility while remaining in the same occupation have decreased over time. So there is a general trend that inter-firm mobility with an occupation change has increased while inter-firm mobility while remaining in the same occupation has decreased. The incidence of being fired while remaining in the same occupation has increased over time, but the overall incidence of this type of inter-firm mobility is very low.

Table 2.1 shows descriptive statistics for the independent variables in the sample. These descriptives capture many of the trends in the broader labor market. For instance, over time we see that the percentage of individuals working part-time has increases as well as the percentage of workers in service and clerical occupations and service industries while the percentage in manual occupations and manufacturing industries has decreased. Interestingly, the occupation and firm tenure stays constant across cohorts. It is important to remember that this is a young sample (ages 18-31 years); these are years when workers tend to be mobile. If we had data on
workers at older ages from the original and middle cohorts we would likely see a decline in the average firm and occupational tenure over time\textsuperscript{16}.

**Regression Results**

Regression coefficients for the original, middle and recent cohorts for the various types of mobility, including interaction terms with education, are presented in Tables 2.2 through 2.4. Coefficients that show the impact on log wages (as for these models) are often interpreted in term of the percentage change in wages, e.g. a coefficient of .02 is interpreted as a one unit change in the independent variable leading to a 2\% change in wages. As Table 2.5 shows, this approximation works very well for coefficients with absolute value <=.1 but for coefficients with absolute value > .1, the approximation slightly over-estimates the effect of negative coefficients and under-estimates the effect of positive coefficients. I discuss the coefficients in terms of the impact on log wages but include Table 2.5 so that the reader can have a handy guide to the way this translates into the more intuitive \% change in wages. Key results from Tables 2.2 through 2.4 are illustrated in Figures 2.3 through 2.8. In each figure, the bars represent model coefficients and the stars above the bars represent statistical significance of those bars. Because Hausman test result showed that the fixed effects coefficients were statistically significant from the random effects coefficients for all three cohorts, I focus the discussion on coefficients from the fixed effects models, except where explicit noted. Throughout the results section I use the shorthand ‘log wages’ to refer to the outcome, log hourly wage rate adjusted by the CPI.

\textsuperscript{16} Because the NLSY oversamples black and Latino workers and over-samples low income workers for the middle cohort, the percentages for race/ethnicity and educational attainment do not match the U.S population.
Involuntary Job Loss

We see from Figure 2.3 that the impact on log wages of first displacement while changing occupation gets progressively worse over time. This ranges from a statistically insignificant -.02 for the original cohort to -.07 for the recent cohort. The difference between the original and recent cohorts is statistically significant (p < .05). However, the negative impact of displacement on wages only occurs when the individual also changes to new occupation. The impact of displacement while remaining in the same occupation is not statistically significant for any cohort. Furthermore, for the middle (p < .05) and recent (p < .1) cohorts, the difference between the impact of first displacement while changing occupations and displacement while remaining in the same occupation is statistically significant\textsuperscript{17}.

We also from Figure 2.3 see that the negative impact of firing on log wages shows a trend of getting progressively worse over time, ranging from -.05 for the original and middle cohorts to -.09 for the recent cohorts, although the differences between cohorts are not statistically significant. The impact of firing while remaining in the same occupation has inconsistent effects; since such a small portion of each sample (1-3\%) has experienced this event, it is difficult to make accurate conclusions.

Figure 2.4 illustrates the proportion of the impact of first displacement and being fired that is a result of the loss of firm and/or occupational tenure. We see from Figure 4 that for the middle cohort, about 75\% of the loss in log wages that results from first displacement and

\textsuperscript{17} The results in this paragraph are for individuals with no bachelor’s degree. For both the original and middle cohort, the interaction term between bachelor’s degree and first displacement with occupation change is positive and statistically significant and in fact appears to result in significant wage gains for individuals in the original cohort and statistically insignificant wage gains for individuals in the middle cohort following displacement. It should be noted that the percentage of individuals experiencing displacement who have a bachelor’s degree is a small percentage of those experiencing displacement. These findings: that while displacement has negative consequences for most individuals there are a small portion of persons who experience wage gains following displacement is consistent with what other researchers have found (personal communication, Jeff Wenger, RAND).
changing occupation is due to loss of tenure, as the coefficient changes from -.04 to -.01 when tenure controls are added. However for the recent cohort, only about 15% of the loss in log wages is due to loss of tenure (coefficient changes from -.07 to -.05). The trends are similar for firing with an occupation change: for the middle cohort, about 50% of the wage loss is due to tenure loss, but for the recent cohort only about 13% of the wage loss can be attributed to loss of tenure. All coefficients from the original models are statistically significantly different (p < .05) from models controlling for firm and occupational tenure, using bootstrapped standard errors.

**Voluntary Inter-Firm Mobility**

Figure 2.5 shows the impact of voluntary inter-firm mobility on wages. The bars on the left show the coefficients for individuals without a bachelor’s degree; the bars on the right show the total effects for individuals with a bachelor’s degree, which is the main effect + the respective interaction term with bachelor’s degree. The most dramatic finding shown in Figure 2.5 is that for the middle and recent cohorts, the positive impact of voluntary inter-firm mobility is much greater for individuals who have a bachelor’s degree. For individuals without a BA, the benefits of inter-firm mobility are small and only occasionally statistically significant: the impact on log wages when changing occupations is .02-.03; it is .02-.05 when remaining in the same occupation. By contrast, for individuals with a BA in the middle and recent cohorts, the impact on log wages when changing occupations is 14-15%; when remaining in the same occupation, it is 18%. For the middle and recent cohorts, all interaction terms between education and voluntary inter-firm mobility are statistically significant (p < .05). For the original cohort, the effect of education is less clear. The bars to the right on Figure 2.5 include the combined main effect + interaction term for the original cohort for purposes of visual comparison, however neither
interaction term is statistically significant at the p < .05 level (the interaction term for remaining in the same occupation is significant at p < .1).

We see from Figure 2.5, that there has been no consistent (or statistically significant) change over time in the effect of voluntary-firm mobility for those without a bachelor’s degree. However for those with a bachelors’ degree, the respective impacts on log wages of voluntary inter-firm mobility with and without an occupation change each increase by about .08 between the original and middle/recent cohorts. These increases could be considered conservative in that they incorporate the interaction terms for the original cohort\(^{18}\). There is negligible change between the middle and recent cohorts however.

Finally, the only statistically significant difference between changing occupation and remaining in the same occupation for voluntary inter-firm mobility occurs for the middle cohort for those without a bachelor’s degree. While for those with a BA in each cohort the differences between changing occupation and remaining in the same occupation appear to be about .03 log wages, these coefficients have rather large standard errors, suggesting a large variance across the population in the impact on log wages.

Figure 2.6 compares the coefficients from Figure 2.5 with the respective coefficients when controls for firm tenure and occupational tenure are added to the model (Model 3). We see that in nearly all cases, the positive impact of voluntary inter-firm mobility on log wages is

\(^{18}\) All changes over time are significant at least at p < .1; most at p < .05:. For persons with a BA, the impact of New Occupation Voluntary is significantly different between the Original Cohort and the Middle and Recent Cohorts (both p < .05). The interaction between BA and New Occupation Voluntary is also significantly different between the Original Cohort and Recent Cohort (p < .05) and the Original and Middle Cohort (p < .1).

For persons with a BA, the impact of Same Occupation Voluntary is significantly different between the Original and Middle Cohort (p < .05) and the Original and Recent Cohort (p < .1). The interaction between BA and Same Occupation Voluntary is also significantly different between the Original and Middle Cohort (p < .05) and Original and Recent Cohort (p < .1).
statistically significantly higher (p < .05) when tenure is controlled for. (The one exception is the original cohort when individuals do not change occupation). This finding is especially important for the middle and recent cohorts for individuals without a bachelors’ degree. For these individuals, whether they change or remain in the same occupation, the positive effects of voluntary inter-firm mobility approximately double when tenure is controlled for, and all effects become statistically significant. This suggests that individuals are moving to firms/occupations which do pay more except that most of that positive benefit is cancelled out by loss of wages due to loss of firm and/or occupational tenure.

Figure 2.7 compares the random effects and fixed effects coefficients for individuals without a bachelor’s degree who change firm and occupation voluntarily. We see that for all three cohorts the random effects coefficients show a worse impact of mobility on log wages than the fixed effects coefficients. Since the random effects coefficients do not control for unobserved characteristics that are stable over time, this suggests that this group of individuals may possess work-related characteristics that serve to suppress their wages. In other words, this is a group of individuals who might not have done well in the labor market regardless of mobility patterns. We see similar patterns for individuals who experience firing, especially when changing occupations, but that is not surprising.

Finally, for individuals in the middle and recent cohorts with no bachelor’s degree, Figure 2.8 compares the fixed coefficients from Model 2 with the respective coefficients when variables for skill differences between current and former occupation are added to the model (Model 4). As noted, Model 4 essentially estimates what the impact of inter-firm mobility would be if the individual could enter a new occupation with exactly the same skills as their former occupation. While this is not exactly realistic, it allows us to assess the extent to which wage loss
which is due to skill differences between occupations and the wage gain that could be approximated by entering an occupation with very similar skills. We see that for first displacement when changing occupation, the negative effect on log wages drops by slightly over 50% for the middle cohort when skill difference variables are added to the model. For the recent cohort the wage loss due to first displacement drops by only about 14% when skill difference variables are added to the model. For firing with a new occupation, the wage loss drops by slightly over 20% for the middle cohort and slightly under 20% for the recent cohort when occupational skill difference variables are added to the model. The results are slightly more dramatic for voluntary inter-firm mobility with an occupation change. Here we look specifically at individuals with no bachelor’s degree. For the middle cohort the wages gains approximately double and for the recent cohort the wages gains more than double (and become statistically significant) when skill differences between occupations are controlled for. For both cohorts differences between coefficients for models with and without skill controls are statistically significantly different (p < .05) using bootstrapped standard errors.

**Summary of Key Findings**

- The negative impact of displacement on wages is restricted to individuals changing occupations.
- The negative impact of displacement has increased over time.
- For the middle recent cohorts, firm and occupational tenure explain a substantial portion of the loss in wages due to displacement and firing. This is somewhat less true for the recent cohort.
- There is a large education differential in the impact of voluntary firm mobility on wages and this has increased over time.
- For the middle and recent cohorts, those without a bachelor’s degree do not generally benefit from voluntary firm mobility and there has been minimal change over time.
• They find ‘higher wage quality’ positions, but the loss of firm and/or occupational tenure cancels out the wage benefits.

• Individuals without a bachelor’s degree who will voluntarily change firm and occupation tend to be those with worse earning prospects to begin with.

• Finding a new occupation with similar skills cancels out some of the wage loss due to displacement and firing and brings substantial benefits when the inter-firm mobility is voluntary.

Discussion and Conclusion

The findings have several implications. First, the findings refine the supposition by Bernhardt et al that the impact of inter-firm mobility on wages for young men worsened over time between the 1970s and 1990s. The findings here suggest that the impact of voluntary inter-firm mobility for those without a bachelor’s degree has remained relatively constant over time. Individuals with a bachelor’s degree see much stronger benefits to voluntary inter-firm mobility today than they did 40 years ago. The negative impact of displacement (and to a certain extent firing) has worsened over time differences but the largest changes only impact the most recent cohort.

Second, loss of tenure and skill differences between occupations explain a greater portion of the wages losses due to displacement and firing for the middle cohort as compared to the recent cohort. This suggests that job loss today has a different quality then it did 20 years ago and highlights variation within the ‘age of precarity’ (e.g. 1975-2015) within the labor market. Those experiencing job loss today appear to simply be unable to find new jobs that are on a par with their former jobs wage-wise, even if the skill sets are similar. Research focusing on the types of jobs individuals have been able to find in the aftermath of the great recession might shed
some light on how the structures and processes underlying displacement and rehiring have changed over time.

Third, if we assume that one of the primary motivating factors for switching firms and/occupation is to increase one’s wages, the fact that individuals without a bachelor’s degree do not tend to benefit wage-wise from voluntary inter-firm mobility suggests that the problem of ‘imperfect information’ frequently occurs when individuals try to project their future wages at a potential new position. In addition, voluntary inter-firm and occupational mobility for individuals without a bachelor’s degree are not efficient. Job searches and learning a new position require effort and it is somewhat problematic that this effort does not bring wage benefits for less well educated individuals.

However, it is true that when tenure is controlled for individuals without a bachelor’s degree do benefit wage-wise from voluntary inter-firm mobility. As mentioned, this suggests that they are finding jobs which in principle pay more, but the loss of occupational and firm tenure cancels out the wage benefits. This suggests that these individuals’ initial occupations and/or firms may have been ‘mis-matches’ for them in terms of wage potential. In this case the efficiency is not in the early-mid-career job search process but in the initial job search process.

In addition, the fact that individuals without a bachelor’s degree who engage in inter-firm mobility are those who likely would do worse in the labor market regardless suggests that we should perhaps re-conceptualize how we think about the concept of voluntary inter-firm mobility. Are these truly ‘voluntary’ changes or do the individuals have a sense of being stagnant at most positons which makes their search somewhat more desperate and hence potentially inefficient.
Several of the aforementioned findings on voluntary inter-firm mobility for individuals without a bachelor’s degree: the potential initial firm/occupation mismatch, the potentially inefficient early-mid-career job search, and the fact these individuals may have trouble adjusting to the labor market in general, suggest that a more active role of workforce development agencies in aiding voluntary job searches could be warranted. The most intensive workforce development services in the United States are usually targeted at individuals who have involuntarily lost a job. But the findings of this research suggests that perhaps it would be beneficial to develop a more active workforce development program for all members of the workforce. The finding that individuals without a bachelor’s degree have much better outcomes from voluntary inter-firm mobility when their new occupation shares skills with their former occupation also indicates that professional intervention to help target the search toward occupations with similar skills might be beneficial.

Finally, while the results confirm the findings of earlier studies that remaining in the same occupation is beneficial to those experiencing displacement, there were almost no significant differences between staying in the same occupation and changing occupation for voluntary inter-firm mobility. For individuals with a bachelor’s degree the average positive effects for voluntary inter-firm mobility when remaining in the same occupation appeared larger than effects for those changing occupations for all three cohorts. But the variance of the estimators was large leading to insignificant differences between types of mobility. This suggests it would be useful to examine the variation across the population in terms of voluntary inter-firm mobility to explore who does well, who does not and what characteristic differentiate the two groups.
Figure 2.2: Percentage of Respondents with at least One Experience of Firm Mobility by Type

- **New Occupation Displaced**
- **Same Occupation Displaced**
- **New Occupation Fire**
- **Same Occupation Fire**
- **New Occupation Voluntary**
- **Same Occupation Voluntary**

- **Original Cohort**
- **Middle Cohort**
- **Recent Cohort**
Table 2.1: Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean (Standard Deviation) or Percentage</th>
<th>Original Cohort (24,161 person-years)</th>
<th>Middle Cohort (40,764 person-years)</th>
<th>Recent Cohort (22,568 person-years)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Black</td>
<td>25%</td>
<td>25%</td>
<td>24%</td>
<td></td>
</tr>
<tr>
<td>Latino</td>
<td>N/A</td>
<td>18%</td>
<td>22%</td>
<td></td>
</tr>
<tr>
<td>Other Race</td>
<td>1%</td>
<td>N/A</td>
<td>N/A</td>
<td></td>
</tr>
<tr>
<td>Multiracial</td>
<td>N/A</td>
<td>N/A</td>
<td>1%</td>
<td></td>
</tr>
<tr>
<td>No High School Diploma</td>
<td>24%</td>
<td>29%</td>
<td>17%</td>
<td></td>
</tr>
<tr>
<td>High School Diploma</td>
<td>39%</td>
<td>42%</td>
<td>37%</td>
<td></td>
</tr>
<tr>
<td>Some College</td>
<td>18%</td>
<td>14%</td>
<td>27%</td>
<td></td>
</tr>
<tr>
<td>Bachelors Degree</td>
<td>19%</td>
<td>15%</td>
<td>19%</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>24.9 (3.6)</td>
<td>25.1 (3.6)</td>
<td>25.5 (3.2)</td>
<td></td>
</tr>
<tr>
<td>Married</td>
<td>63%</td>
<td>38%</td>
<td>23%</td>
<td></td>
</tr>
<tr>
<td>Never Been Married</td>
<td>28%</td>
<td>54%</td>
<td>73%</td>
<td></td>
</tr>
<tr>
<td>Widowed/Divorced/Separated</td>
<td>9%</td>
<td>8%</td>
<td>4%</td>
<td></td>
</tr>
<tr>
<td>Work Experience (weeks)</td>
<td>219 (132)</td>
<td>396 (179)</td>
<td>319 (166)</td>
<td></td>
</tr>
<tr>
<td>Part Time Worker</td>
<td>5%</td>
<td>15%</td>
<td>19%</td>
<td></td>
</tr>
<tr>
<td>Firm Tenure (years)</td>
<td>2.1 (2.3)</td>
<td>3.0 (2.6)</td>
<td>2.8 (2.4)</td>
<td></td>
</tr>
<tr>
<td>Occupation Tenure (years)</td>
<td>2.1 (1.5)</td>
<td>2.1 (1.7)</td>
<td>2.5 (1.9)</td>
<td></td>
</tr>
<tr>
<td>Occupations:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manager</td>
<td>8%</td>
<td>8%</td>
<td>7%</td>
<td></td>
</tr>
<tr>
<td>Professional/Technical</td>
<td>16%</td>
<td>11%</td>
<td>13%</td>
<td></td>
</tr>
<tr>
<td>Service</td>
<td>6%</td>
<td>14%</td>
<td>20%</td>
<td></td>
</tr>
<tr>
<td>Sales</td>
<td>5%</td>
<td>3%</td>
<td>10%</td>
<td></td>
</tr>
<tr>
<td>Clerical</td>
<td>8%</td>
<td>9%</td>
<td>11%</td>
<td></td>
</tr>
<tr>
<td>Craft</td>
<td>20%</td>
<td>20%</td>
<td>17%</td>
<td></td>
</tr>
<tr>
<td>Operator/Laborer</td>
<td>37%</td>
<td>35%</td>
<td>21%</td>
<td></td>
</tr>
<tr>
<td>Industries:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture/Mining</td>
<td>4%</td>
<td>5%</td>
<td>2%</td>
<td></td>
</tr>
<tr>
<td>Construction</td>
<td>10%</td>
<td>12%</td>
<td>12%</td>
<td></td>
</tr>
<tr>
<td>Manufacturing</td>
<td>35%</td>
<td>25%</td>
<td>12%</td>
<td></td>
</tr>
<tr>
<td>Wholesale and Retail Trade</td>
<td>17%</td>
<td>22%</td>
<td>18%</td>
<td></td>
</tr>
<tr>
<td>Transportation/Warehousing/Utilities/Communications</td>
<td>8%</td>
<td>7%</td>
<td>9%</td>
<td></td>
</tr>
<tr>
<td>Finance/Insurance/Real Estate</td>
<td>4%</td>
<td>3%</td>
<td>5%</td>
<td></td>
</tr>
<tr>
<td>Service Industries (Business, Repair, Education, Health, Social)</td>
<td>16%</td>
<td>20%</td>
<td>40%</td>
<td></td>
</tr>
<tr>
<td>Services, Arts, Entertainment, Personal</td>
<td>6%</td>
<td>5%</td>
<td>3%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Model 1: RE</td>
<td></td>
<td>Model 2: FE</td>
<td></td>
</tr>
<tr>
<td>--------------------------------------</td>
<td>------------</td>
<td>----------------------</td>
<td>------------</td>
<td>----------------------</td>
</tr>
<tr>
<td></td>
<td>Coeff</td>
<td>SE</td>
<td>Coeff</td>
<td>SE</td>
</tr>
<tr>
<td>New Occupation First Displacement</td>
<td>-0.014</td>
<td>(0.015)</td>
<td>-0.019</td>
<td>(0.017)</td>
</tr>
<tr>
<td>New Occupation Subsequent Displ.</td>
<td>-0.001</td>
<td>(0.023)</td>
<td>0.003</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Same Occupation Layoff</td>
<td>0.029</td>
<td>(0.018)</td>
<td>0.015</td>
<td>(0.020)</td>
</tr>
<tr>
<td>New Occupation Fire</td>
<td>-0.044+</td>
<td>(0.023)</td>
<td>-0.053+</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Same Occupation Fire</td>
<td>-0.031</td>
<td>(0.048)</td>
<td>-0.060</td>
<td>(0.055)</td>
</tr>
<tr>
<td>New Occupation Voluntary</td>
<td>0.016+</td>
<td>(0.009)</td>
<td>0.024*</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Same Occupation Voluntary</td>
<td>0.041**</td>
<td>(0.012)</td>
<td>0.030*</td>
<td>(0.013)</td>
</tr>
<tr>
<td>New Occupation Voluntary*BA</td>
<td>-0.009</td>
<td>(0.021)</td>
<td>0.034</td>
<td>(0.024)</td>
</tr>
<tr>
<td>Same Occupation Voluntary*BA</td>
<td>0.052+</td>
<td>(0.027)</td>
<td>0.057+</td>
<td>(0.029)</td>
</tr>
<tr>
<td>New Occupation Layoff*BA</td>
<td>0.084*</td>
<td>(0.042)</td>
<td>0.135**</td>
<td>(0.045)</td>
</tr>
</tbody>
</table>

* p < .05, ** p < .01, *** p < .001, + p < .1
Table 2.3: Regression Models Middle Cohort

<table>
<thead>
<tr>
<th></th>
<th>Model 1: RE</th>
<th></th>
<th>Model 2: FE</th>
<th></th>
<th>Model 3: FE w/ Tenure</th>
<th></th>
<th>Model 4: FE w/ Skills</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff</td>
<td>SE</td>
<td>Coeff</td>
<td>SE</td>
<td>Coeff</td>
<td>SE</td>
<td>Coeff</td>
<td>SE</td>
</tr>
<tr>
<td>New Occupation First Displ.</td>
<td>-0.042***</td>
<td>(0.009)</td>
<td>-0.037***</td>
<td>(0.010)</td>
<td>-0.009</td>
<td>(0.010)</td>
<td>-0.016</td>
<td>(0.010)</td>
</tr>
<tr>
<td>New Occupation Subseq. Displ.</td>
<td>-0.021**</td>
<td>(0.007)</td>
<td>-0.015+</td>
<td>(0.008)</td>
<td>-0.003</td>
<td>(0.008)</td>
<td>-0.016*</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Same Occupation Layoff</td>
<td>0.025</td>
<td>(0.018)</td>
<td>0.016</td>
<td>(0.020)</td>
<td>0.036+</td>
<td>(0.019)</td>
<td>0.007</td>
<td>(0.019)</td>
</tr>
<tr>
<td>New Occupation Fire</td>
<td>-0.074***</td>
<td>(0.013)</td>
<td>-0.054***</td>
<td>(0.015)</td>
<td>-0.027+</td>
<td>(0.015)</td>
<td>-0.038**</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Same Occupation Fire</td>
<td>0.003</td>
<td>(0.032)</td>
<td>0.005</td>
<td>(0.036)</td>
<td>0.037</td>
<td>(0.036)</td>
<td>0.004</td>
<td>(0.035)</td>
</tr>
<tr>
<td>New Occupation Voluntary</td>
<td>0.018*</td>
<td>(0.008)</td>
<td>0.048***</td>
<td>(0.009)</td>
<td>0.092***</td>
<td>(0.009)</td>
<td>0.090***</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Same Occupation Voluntary</td>
<td>0.021+</td>
<td>(0.011)</td>
<td>0.019</td>
<td>(0.012)</td>
<td>0.056***</td>
<td>(0.012)</td>
<td>0.011</td>
<td>(0.012)</td>
</tr>
<tr>
<td>New Occupation Voluntary*BA</td>
<td>0.054**</td>
<td>(0.021)</td>
<td>0.094***</td>
<td>(0.023)</td>
<td>0.097***</td>
<td>(0.023)</td>
<td>0.100***</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Same Occupation Voluntary*BA</td>
<td>0.158***</td>
<td>(0.026)</td>
<td>0.165***</td>
<td>(0.029)</td>
<td>0.160***</td>
<td>(0.029)</td>
<td>0.163***</td>
<td>(0.029)</td>
</tr>
<tr>
<td>New Occupation Layoff*BA</td>
<td>0.031</td>
<td>(0.027)</td>
<td>0.065*</td>
<td>(0.031)</td>
<td>0.061+</td>
<td>(0.031)</td>
<td>0.071*</td>
<td>(0.031)</td>
</tr>
</tbody>
</table>

*p < .05, ** p < .01, *** p < .001, + p < .1
Table 2.4: Regression Models: Recent Cohort

<table>
<thead>
<tr>
<th></th>
<th>Model 1: RE</th>
<th>Model 2: FE</th>
<th>Model 3: FE w/ Tenure</th>
<th>Model 4: FE w/ Skills</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff</td>
<td>SE</td>
<td>Coeff</td>
<td>SE</td>
</tr>
<tr>
<td>New Occupation First Displacement</td>
<td>-0.074***</td>
<td>(0.014)</td>
<td>-0.068***</td>
<td>(0.017)</td>
</tr>
<tr>
<td>New Occupation Subsequent Displ.</td>
<td>-0.030</td>
<td>(0.019)</td>
<td>-0.035</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Same Occupation Layoff</td>
<td>0.015</td>
<td>(0.025)</td>
<td>-0.007</td>
<td>(0.030)</td>
</tr>
<tr>
<td>New Occupation Fire</td>
<td>-0.107***</td>
<td>(0.016)</td>
<td>-0.087***</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Same Occupation Fire</td>
<td>-0.064*</td>
<td>(0.027)</td>
<td>-0.052+</td>
<td>(0.030)</td>
</tr>
<tr>
<td>New Occupation Voluntary</td>
<td>-0.023*</td>
<td>(0.011)</td>
<td>0.015</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Same Occupation Voluntary</td>
<td>0.017</td>
<td>(0.016)</td>
<td>0.033+</td>
<td>(0.019)</td>
</tr>
<tr>
<td>New Occupation Voluntary*BA</td>
<td>0.082**</td>
<td>(0.026)</td>
<td>0.135***</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Same Occupation Voluntary*BA</td>
<td>0.114**</td>
<td>(0.041)</td>
<td>0.148***</td>
<td>(0.046)</td>
</tr>
<tr>
<td>New Occupation Layoff*BA</td>
<td>0.042</td>
<td>(0.039)</td>
<td>0.058</td>
<td>(0.047)</td>
</tr>
</tbody>
</table>

* p < .05, ** p < .01, *** p < .001, + p < .1
Table 2.5: Impact on Wages and Log Wages

<table>
<thead>
<tr>
<th>Impact on log wages</th>
<th>Impact on wages</th>
<th>Impact on log wages</th>
<th>Impact on wages</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01</td>
<td>0.01</td>
<td>-0.01</td>
<td>-0.01</td>
</tr>
<tr>
<td>0.02</td>
<td>0.02</td>
<td>-0.02</td>
<td>-0.02</td>
</tr>
<tr>
<td>0.03</td>
<td>0.03</td>
<td>-0.03</td>
<td>-0.03</td>
</tr>
<tr>
<td>0.04</td>
<td>0.04</td>
<td>-0.04</td>
<td>-0.04</td>
</tr>
<tr>
<td>0.05</td>
<td>0.05</td>
<td>-0.05</td>
<td>-0.05</td>
</tr>
<tr>
<td>0.06</td>
<td>0.06</td>
<td>-0.06</td>
<td>-0.06</td>
</tr>
<tr>
<td>0.07</td>
<td>0.07</td>
<td>-0.07</td>
<td>-0.07</td>
</tr>
<tr>
<td>0.08</td>
<td>0.08</td>
<td>-0.08</td>
<td>-0.08</td>
</tr>
<tr>
<td>0.09</td>
<td>0.09</td>
<td>-0.09</td>
<td>-0.09</td>
</tr>
<tr>
<td>0.1</td>
<td>0.11</td>
<td>-0.1</td>
<td>-0.10</td>
</tr>
<tr>
<td>0.11</td>
<td>0.12</td>
<td>-0.11</td>
<td>-0.10</td>
</tr>
<tr>
<td>0.12</td>
<td>0.13</td>
<td>-0.12</td>
<td>-0.11</td>
</tr>
<tr>
<td>0.13</td>
<td>0.14</td>
<td>-0.13</td>
<td>-0.12</td>
</tr>
<tr>
<td>0.14</td>
<td>0.15</td>
<td>-0.14</td>
<td>-0.13</td>
</tr>
<tr>
<td>0.15</td>
<td>0.16</td>
<td>-0.15</td>
<td>-0.14</td>
</tr>
<tr>
<td>0.16</td>
<td>0.17</td>
<td>-0.16</td>
<td>-0.15</td>
</tr>
<tr>
<td>0.17</td>
<td>0.19</td>
<td>-0.17</td>
<td>-0.16</td>
</tr>
<tr>
<td>0.18</td>
<td>0.20</td>
<td>-0.18</td>
<td>-0.16</td>
</tr>
<tr>
<td>0.19</td>
<td>0.21</td>
<td>-0.19</td>
<td>-0.17</td>
</tr>
<tr>
<td>0.2</td>
<td>0.22</td>
<td>-0.2</td>
<td>-0.18</td>
</tr>
<tr>
<td>0.21</td>
<td>0.23</td>
<td>-0.21</td>
<td>-0.19</td>
</tr>
<tr>
<td>0.22</td>
<td>0.25</td>
<td>-0.22</td>
<td>-0.20</td>
</tr>
<tr>
<td>0.23</td>
<td>0.26</td>
<td>-0.23</td>
<td>-0.21</td>
</tr>
<tr>
<td>0.24</td>
<td>0.27</td>
<td>-0.24</td>
<td>-0.21</td>
</tr>
<tr>
<td>0.25</td>
<td>0.28</td>
<td>-0.25</td>
<td>-0.22</td>
</tr>
<tr>
<td>0.26</td>
<td>0.30</td>
<td>-0.26</td>
<td>-0.23</td>
</tr>
<tr>
<td>0.27</td>
<td>0.31</td>
<td>-0.27</td>
<td>-0.24</td>
</tr>
<tr>
<td>0.28</td>
<td>0.32</td>
<td>-0.28</td>
<td>-0.24</td>
</tr>
<tr>
<td>0.29</td>
<td>0.34</td>
<td>-0.29</td>
<td>-0.25</td>
</tr>
<tr>
<td>0.3</td>
<td>0.35</td>
<td>-0.3</td>
<td>-0.26</td>
</tr>
<tr>
<td>0.31</td>
<td>0.36</td>
<td>-0.31</td>
<td>-0.27</td>
</tr>
</tbody>
</table>
Figure 2.3 Impact of Involuntary Mobility on Log Wages

* p < .05; + p < .1

Figure shows Fixed Effects Coefficients from Model 2.
New Occupation First Displacement for individuals without a Bachelor’s Degree.
* p < .05; + p < .1

Figure shows Fixed Effects Coefficients from Models 2 and 3.
New Occupation First Displacement for individuals without a Bachelor’s Degree.
* p < .05; + p < .1  Figure shows Fixed Effects Coefficients from Model 2.  For persons w/ BA bar is main effect + interaction term.
Figure 2.6: Impact of Voluntary Firm Mobility on Log Wages: Total Effect and Net of Tenure

* p < .05; + p < .1

Figure shows Fixed Effects Coefficients from Models 2 and 3.
For persons w/ BA bar is main effect + interaction term.
Figure 2.7: Impact of Voluntary Occupation Change for Individuals without a BA

* p < .05; + p < .1

Figure shows Random Effects Coefficients and Fixed Effects Coefficients from Model 2.
Figure 2.8: Occupation Skill Differences and the Impact of Occupational Mobility

* p < .05; + p < .1

The figure shows Fixed Effects Coefficients from Models 2 and 4.

For New Occupation, First Displacement and New Occupation Voluntary, coefficients for individuals with no BA.

Introduction

This paper will also examine the impact on wages of voluntary and involuntary inter-firm mobility, with and without concurrent occupational mobility, and the extent to which these patterns vary according to the educational attainment of the worker. However in this paper I use a life course perspective, examining a single cohort of workers through age 55. While much inter-firm and occupational mobility may occur within the early working years, these changes also occur throughout an employee’s working life (Carr and Sheridan 2001). Taking a life course perspective allows for an examination of how the impact of inter-firm mobility events with and without occupation changes vary with the age at which they occur in an individual’s life. In addition, the longer time frame for which respondents are surveyed in the second paper allows for an examination the extent to which the impact of an inter-firm mobility event on an individual’s wages may dissipate or possibly increase over time, resulting in scarring effects.

For this paper, I will examine patterns for both men and women of the second cohort (born 1958-1965) from ages 18 to 55. I will focus on how the impact of the various types of mobility on wages vary according to gender. Due to the various forms of gender inequality present in the labor market, such as occupational segregation of women into lower paying occupations, the fact that within occupations, women are less likely to receive promotions (Petersen and Sapporta 2004), and the existence of hiring ‘queues’ that favor the hiring or men
for higher paying and prestigious positions, we might expect that the impact of the various forms of mobility would vary between women and men. I will explore the extent to which any gender differences in the impact of inter-firm mobility on wages can be explained by either 1) individual level gender inequality and 2) gender based occupational segregation in the labor market.

**Literature Review**

The literature from the first dissertation paper on the impact of voluntary and involuntary inter-firm and occupation changes on wages also apply here, but I will not repeat discussion of those articles.

*Inter-Firm Mobility: Age at which the Mobility Occurs*

Research that examines the separations in a more detailed manner suggests that the impact of involuntary job loss worsens with age and years in the labor market at the time of job loss (Fuller 2008, Mincer and Jovanovic, 1981, Gangl 2006), which is consistent with the specific literature on worker displacement (Von Wachter Song and Manchester 2009). Research has also suggested that the benefits of voluntary firm mobility may be restricted to early years in the labor market (Fuller 2008, Perticara 2002). Thus there is a general trend that the impact of inter-firm mobility in general worsens as a function of the age the worker is when it occurs; voluntary changes are less beneficial and involuntary changes are more detrimental. These findings are not surprising given that older workers tend to earn more due to their work experience, firm tenure and occupational tenure, the latter two of which disappear when inter-firm mobility (with an occupation change) occurs. Firms also may more reluctant to hire older
workers. Since older workers are less in demand, they may be forced to accept positions which pay less.

However it is not known how the impact specifically of inter-firm mobility with and occupation change and inter-firm mobility while remaining in the same occupation may change over the life course. In particular, we saw in the first paper that for young workers, there was very little difference in the impact of voluntary inter-firm mobility with and without an occupation change. However as discussed, a wide body of research has shown that the wage returns to occupation tenure are very strong. In particular, researchers have compared the impact of occupational tenure to industry and firm tenure, with findings that occupational tenure is by far the most important. Kambourov and Manovskii (2009), Yamaguichi (2010), Pavan (2011). Returns to occupational and firm tenure vary by education as well as occupation. For instance, Sullivan (2010) found that returns to occupational tenure were much larger for professional craft and service occupations as compared to clerical, labor and operative occupations. Yamaguichi (2010) found that over the first 10 years of labor market experience, for those with a high school diploma, career tenure (defined by years in the same occupation and industry) accounted for a 13% increase in wages while employer tenure only accounted for a 5% increase in wages. For individuals with a bachelor’s degree, the difference was even larger; career tenure accounts for 18% increase in wages while employer tenure accounted for < 1%.

Due to these findings we might expect that when voluntary inter-firm mobility occur later in the life course, staying in the same occupation may be more beneficial than changing occupation as well. This difference may be particularly pronounced for more educated workers.
As was discussed in the first dissertation paper, workers experiencing displacement who change occupations earn significantly lower wages in their subsequent jobs for a number of reasons including the fact that they may have been ‘over-paid’ relative to market value in their prior firm or industry as well as the fact that after a spell of unemployment they were willing to accept a job paying a lower wage. They also lose any wage benefits of firm and possibly occupational tenure. However over time, these workers likely have the opportunity to adjust to their new firm and occupation, learning new occupation specific skills, and potentially eventually voluntarily moving to a new firm or occupation that pays higher wages. Therefore we might expect that the wage loss due to displacement would ameliorate somewhat over time.

Research suggests that the wage loss following displacement eventually abates slightly, but not for a significant period of time. Kletzer and Farlie (2003) and Stevens (1997) actually found that the wage loss following displacement increased as a function of time since displacement but they only followed workers for 5-6 years after the initial job loss. Research that follows workers for up to 22 years following displacement found wages loses of up to 20% that wages slowly recover over time by about 2-5 percentage points (Till Von Wachter et al 2009). Thus wage loss following displacement appears to persist for a long period, resulting in a ‘scarring effect’ although this does eventually dissipate slightly.

For voluntary inter-firm mobility which involves an occupational switch, we might expect the opposite, namely that potential benefits might not be immediately apparent. Workers will lose the wage returns to occupational and firm tenure when they initially start a job. Over time as they adjust to the new occupation and develop occupation specific skills, they become more valuable to their employer and their wages will likely increase. There is some evidence that
this pattern holds true over the first 10 years following voluntary inter-firm mobility although the data is 40 years old and the authors do not control for whether the individual also changed occupations (Mincer and Jovanovic 1981).

Voluntary Inter-Firm Mobility: Gender Differences: Theory

There are at least five different reasons why we might expect the impact of voluntary inter-firm mobility to vary between men and women these are 1) compensating differentials 2) reluctance of women to negotiate for higher wages, 3) stereotypes held by employers regarding the relative skills talents of women and men 4) intra-firm promotion practices 5) differing social networks between men and women and 6) gender based occupational segregation. The first five aforementioned factors conceptualize gender differences at the individual level in that they focus on the preferences, behavior, and resources of individual women and men. The final factor focuses not on individual persons but on gender inequalities in the structure of the labor market, more specifically gender differences between occupational categories.

Compensating Differentials: The theory of compensating differentials posits that, for a given level of educational and skill requirements, jobs that are more comfortable, less hazardous, require fewer hours or permit a more flexible work schedule will pay less money. This is based on micro-economic principles that less comfortable jobs pay more in order to convince workers to take them. Essentially workers must make the trade-off between wages and the other benefits of the job. The theory has been applied to the gender wage gap to suggest that women are more likely to value non-financial characteristics of the job. In particular, women with children are thought to choose occupations which pay less but allow them to balance work and family demands (England et al 1994, Budig and England 2001).
However, data generally do not supporting the theory of compensating differentials as applied to the gender wage gap (Kaufman 2002). For instance, England et al (1994), found that jobs which were more hazardous and involved less comfortable conditions such as especially high or low temperatures, paid less than other jobs. In addition, physical conditions explained only 2% of the gender wage gap. The one element of compensating differentials theory which has had consistent support from the literature is the choice by women (in particularly mothers) to hold jobs which offer the opportunity for part time work (Kaufman 2002). For instance, Budig and England (2001) found that part time work explained approximately 7% of the wage gap in hourly earnings between mothers and women without children.

**Gender and Negotiation:** A wide body of research has supported these claims that women then who enter a new position are less likely than men to negotiate for higher wages (Babcock 2007). For instance, Leibbrandt (2012) field experiment methods found that women offered a job are less likely to negotiate salary then men unless a job ad explicitly mentions that the salary is negotiable. Women may fear being perceived as too aggressive if they ask for more money, a fear which is not entirely unfounded. In a laboratory experiment, Babcock (2007) found that both men and women viewing videos of men and women negotiating salaries were more likely to form negative opinions of the women than the men.

**Employers and Gender Based Stereotypes:** Employers may hold beliefs that women and men are more suitable or inherently skilled for different types of positions (Reskin 2000). Some such stereotypes are that women are more suited for jobs using routine skills (which tend to pay less) and men are more naturally skilled at mathematical thinking. This results in the creation of gender based labor market queues, where for there will be a preference for hiring men for positions that are considered a better fit for men’s abilities. Frequently these positions are
bring higher pay and more prestige (Reskin 1990). Case study research of specific establishments has supported the existence of gender-based labor market queues. Fernandez and Mors (2008), conducting research on a financial services institution in 1995-6, found that, queues serve to sort women and men into relatively lower and higher paying jobs. Women were disproportionately (relative to the number of female applicants) hired for lower paying jobs and were under-represented (relative to the number of female applicants) for higher paying jobs Fernandez and Mors (2008) and are disproportionately hired in general relative to their post-hiring ratings by employers (Petersen et al 2005). While gender queues are usually used as an explanation for occupational segregation, the concept could also be applied to women changing firms within a specific occupation.

Gender-based stereotyping can lead to both lack of willingness on the part of employers to hire women for specific types of positions as well as reluctance to promote women within a specific firm. However there is evidence that stereotyping is stronger when the individuals do not know each other well and thus this may be more of an issue in the hiring process where hiring managers may not have first-hand knowledge of the applicants skills and abilities (Dovidio and Gaertner 2000, Bidwell 2011).

**Gender and Internal Promotion.** Gender inequality in intra-firm promotion is important to consider as well however, as if women have smaller wage gains then men both when changing firms and occupations and when remaining at a single firm, the two factors will cancel each other in terms of gender differences in the impact of inter-firm mobility. Promotion and the associated wage potential is typically awarded at least in part on the basis of seniority and on average women have less firm tenure and labor market experience than men due to breaks from the labor force at the time of childbirth and after (Kronberg 2014). Even net of labor market experience,
women may be at a disadvantage however. Petersen and Saporta (2004), found that, female employees were less likely to be promoted than male employees with comparable work-related histories. This difference in promotions was associated with a widening gender wage gap over time.

Gender and Social Networks. A wide body of research has established the importance of social networks in the labor market. Members of social networks provide resources including information about current openings, introductions to hiring managers and may influence the hiring decision process (Fernandez and Weinberg 1996, Petersen et al, 2000). While using one’s social network to find a job is not associated with an increase in wages overall (Mouw 2002), the presence of what is termed ‘influential contacts’ in an individual’s social network, is associated with an increase in wages. For instance when a member of an individual’s social network has authority in the hiring process, this is associated with an increase in wages relative to finding a job on one’s own (Kmec and Trimble, 2009, Smith 2000, Seidel Polzer and Stewart 2000). There is some research that suggests that men have a greater number of influential contacts than women, net of characteristics such as employment status and education level. Men are more likely to have professional advisers and consultants in their network (Moore 1990) and within workplace organizations were more likely to have direct ties to persons in positions of authority (Ibarra 1992).

Occupational Segregation. It is well established that women are over-represented in lower paying occupations and under-represented in higher paying occupations. Using 3 digit census occupational codes, the index of dissimilarity for occupational segregation was 57 in 1970, 53 in 1980; 49 in 1990 and 47 in 2000. (Cotter, Hermsen and Vanneman 2004). The index of dissimilarity represents the percentage of women (or men) who would have to change jobs for
the occupational distribution to be the same across the genders. While there has been a decline in
gender occupational segregation over time, occupations remain relatively segregated by gender.
Occupational segregation is strongly related to the gender wage gap, even after controlling for
human capital characteristics, a finding which has been documented by numerous studies

Because women tend to be concentrated in occupations which pay less, it is not
unreasonable to expect that these occupations may also provide less opportunity to increase
wages via inter-firm mobility between occupations. Furthermore, to the extent that when women
change occupations they tend to move between relatively lower paying occupations, this would
also potentially result in lower gains to inter-firm mobility that involves an occupation change.
The important distinction between the role of occupational segregation and all of the
aforementioned factors is that the gender differences here in the impact of inter-firm mobility on
wages do not directly result from gender differences in behavior or treatment of individual
women and men but rather their differing occupational locations in the labor market and the
wage opportunities associated with those occupations.\(^{19}\).

**The Role of Education:** Based on the aforementioned factors, there are also several
reasons why we might an interaction effect between gender and education in terms of the impact
of voluntary inter-firm mobility on wages. The direction of that interaction is not clear however,
as the various factors suggest contradictory effects. For instance, occupational segregation by
gender is higher among individuals without a bachelor’s degree (England 2010). However, the
variance in wages is higher among occupations which require a bachelor’s degree. As a result,
the relationship between occupational segregation and the gender wage gap is likely higher for

\(^{19}\) Occupational segregation is based on the voluntary or involuntary decisions of individual men and women to
choose specific occupations but the direct effect is the characteristics of the occupations.
occupations which require a bachelor’s degree. In addition, the impact of salary negotiation on wages may be stronger for occupations which require a college degree. On the other hand, it is possible that hiring managers may rely less on gender based stereotypes when hiring for positions which require a bachelor’s degree.

Involuntary Inter-Firm Mobility: Gender Differences: Theory

For involuntary firm mobility, such as layoffs and firing theoretical expectations about gender differences are more complicated. In principle, the factors mentioned above could all contribute to women suffering worse wage losses then men following involuntary job loss. However this is mitigated by the fact that individual have less choice in their occupation and firm following involuntary job loss. In addition, since men have higher wages overall, men who are displaced may have a higher pre-displacement wage then women, thus there is a greater opportunity for them to have significant wage losses. Furthermore, manufacturing industries, which have the highest rates of displacement and the highest wage losses following displacement, are disproportionately populated by men Von Wachter, Till, Jae Song and Joyce Manchester (2009).

Inter-Firm Mobility: Gender Differences: Results

We know that voluntary inter-firm mobility tends to have a positive effect on wages whereas the impact of involuntary job loss is negative. Furthermore, men are more likely than women to experience involuntary job loss, while the rates of voluntary inter-firm mobility are comparable between men and women (my own calculations). Therefore, research which does not distinguish between voluntary and involuntary inter-firm mobility will be confounded by the fact
of a higher proportion of the mobile men having experienced mobility that is involuntary. Therefore I focus on research that distinguishes between these two types of mobility.

Research exploring gender differences in the impact of displacement (layoffs, plant closures) and firing on wages are inconsistent. Ruhm (1987) and Fuller (2008) found that the impact of layoffs and firings were generally worse for men than for women, although Spalter-Roth and Deitch (1999) found that the impact of displacement was worse for women than for men, and Keith and McWilliams (1999) found that the impact of displacement or firing by gender. Research examining gender differences in the impact of voluntary inter-firm mobility on wages is also inconsistent. Some research suggests that voluntary inter-firm mobility brings greater wage gains for men than for women (Ruhm 1987, Light 2005) although other research found no gender differences (Fuller 2008, Keith and McWilliams 1995).

It is possible that age range of the various samples, the time respondents were followed subsequent to an inter-firm mobility event, or the modeling strategy (Spalter-Roth and Deitch used an instrumental variable method while the other authors do not appear to address issues of endogeneity) may contribute to these differences but it is not immediately clear how. The overall conclusion is that estimates of gender differences in the impact of displacement and firing on wages are sensitive to decisions regarding the sample, measures and modelling strategy. The sample I use will include inter-firm mobility events at a wide range of ages and follow individuals for a significant period of time following displacement and discharge and I will control for both of these factors.

Research does consistently suggest that firm switches for family reasons (e.g. the birth of a child) have a negative impact on wages for women but not for men. These types of firm
changes are also much more common among women (Keith and McWilliams, 1995; Fuller, 2008).

None of the aforementioned studies control for differing effects by education or whether or not the inter-firm mobility event also includes an occupational change.

Summary on Inter-Firm and Occupational Mobility by Gender, Age and Time Since Mobility

What we know:

- The impact of displacement on wages is worse when displacement occurs at older ages.
- The benefit of voluntary inter-firm mobility on wages is less beneficial when the mobility occurs at older ages.
- The impact of displacement on wages persists for a long time following displacement but does slightly abate with time.
- The impact of inter-firm mobility which occurs for family related reasons has a negative impact for women but not for men.

What we do not know:

- How differences in the impact on wages between voluntary inter-firm mobility with an occupation change and voluntary inter-firm mobility without an occupation change might be moderated by the age at which the inter-firm mobility takes place.
- How the impact of voluntary inter-firm mobility with an occupation change on wages may change based on the duration of time since the inter-firm mobility event.
- How the impact of displacement and firing on wages varies between men and women.
- How the impact of voluntary inter-firm mobility on wages varies between men and women.
- How the relationship between education and the impact of voluntary inter-firm mobility on wages varies between men and women.
- To the extent that gender differences occur, can they be explained by 1) treatment and behavior of individual women or 2) occupational segregation

20 I did not copy the bullets from the first dissertation paper but most of them apply here as well.
Research Questions

This paper will focus on the following research questions:

- What are the impacts on wages for workers over the life course of?
  - voluntary inter-firm mobility while remaining in the same occupation
  - voluntary inter-firm mobility while changing occupations
  - involuntary inter-firm mobility while remaining in the same occupation,
  - involuntary inter-firm mobility while changing occupations

- How do the above findings vary by educational attainment?

- How do the above findings vary by the age at which inter-firm mobility occurs?

- How do the above findings vary by the duration of time since the inter-firm mobility?

- How do the above findings vary by gender?

- To what degree can gender differences be explained by 1) treatment and behavior of individual women or 2) occupational segregation

Figure 3.1 presents a diagram of the conceptual model for my analysis.

Data and Methods

Much of the data and methods for this paper are identical to the first dissertation paper. I therefore describe what I did, but I do not repeat the rationales for similar modeling strategies, the math behind the fixed effects model etc.

Sample

I will use the NLSY79 data set. However as the goal of this paper is to examine the impact of various types of firm mobility across the life course, I will include the entire NLSY79 data set (1979-2012). For this sample of 8579 men and 9002 women, I will use respondent data
from ages 18 to 55, with individuals under age 23 who are still in school excluded. From 1979-1994, the NLSY79 includes surveys for every year. However from 1994-2012, the survey was conducted every other year, in even years only. I will discuss this issue further in the section on sensitivity tests. When the entire range of ages in the NLSY79 data set is used, the response rate (for living respondents) drops somewhat, to 79% by 2012.

Variables

The outcome will be the log hourly wage rate, adjusted by the CPI. I use standard controls used in models with wage outcomes including calendar year, education (no high school diploma, high school diploma, some college, bachelor’s degree or higher), race/ethnicity (white, black, Latino, multiracial, other), lifetime weeks of work experience, occupation (1 digit categories), industry (1 digit categories), firm tenure (years), lifetime occupation tenure (years), marital status. I also include variables for if there is a child under the age of 18 in the household and a child under the age of 5 in the household. Calendar year is modeled as a series of 0/1 indicator variables for each year.

I measure inter-firm mobility by a 10 category variable. Six of the categories are the same as for the first dissertation paper: 1) remained in same firm, 2) displacement from previous firm and remained in same occupation at subsequent position 3) displacement from previous firm and changed occupation at subsequent position 4) fired from previous firm and remained in

---

21 As with paper 1, I exclude the military sample.

22 The NLSY does not collect information on whether a respondent is Asian American or Native American specifically. Multiracial is only available in the NLSY 97. Other is only available in NLSY Young Men. Asian American and Native American appear to be lumped with white in NLSY79 and NLSY97.

23 As with paper 1, I define a displacement as an involuntary job loss that is not related to the characteristics of the employee e.g. (layoff, plant closure, layoff, end of temporary job).
same occupation at subsequent position 5) fired from previous firm and changed occupation at new firm 6) changed firm voluntarily and remained in same occupation at subsequent position. The variable also has four new categories. Changing firms voluntarily with a new occupation is divided into two categories: 7) changing into a new occupation that is managerial in nature and 8) changing to a new occupation that is not managerial in nature. Because this sample includes women, I also add the following two variables 9) changed firm due to family reasons (e.g. marriage, pregnancy, birth of a child) and remained in same occupation at subsequent position and 10) changed firm due to family reasons and changed occupation at new firm.

My actual measure consists of 9 variables, each measuring whether the specific type of inter-firm mobility has occurred at least once before the survey year. For this paper, I distinguish each type of inter-firm mobility based on whether the mobility occurred before age 30 or at age 30 and older. For displacement with a new occupation, I also distinguish mobility events that occurred after age 40. Therefore this type of mobility is measured separately for three age groups: before age 30, age 30-39 and after age 40. I conducted sensitivity tests where I modeled the other types of mobility distinguishing events that occurred after age 40 from events age 30-39 but the coefficients for events occurring at the two age groups were nearly identical.

Therefore, my model includes 19 actual variables. The 9 variables for inter-firm mobility occurring before age 30 capture whether the respondent has experienced at least one inter-firm mobility event since age 18 or completing full time schooling. The 8 variables for inter-firm mobility events at age 30 or older capture whether the respondent has experienced at least one mobility event after age 30.

---

24 I do not include this variable in paper 1, in part because the NLSY Young Men does not distinguish these types of moves from other voluntary firm moves. In comparing the results for the NLSY79 men aged 18-30 when this variable is or is not used, the differences are tiny. Therefore it does not appear problematic to exclude the variable for paper 1.

25 When individuals are younger than 30 they have a value of 0 for whether an inter-firm mobility event has occurred later than age 30.
interfirm mobility event since age 30. The variable for displacement with a new occupation age 30-39 and age 40 or older capture whether the respondent has been displaced and concurrently changed occupation at least once during ages 30-39 and at age 40 or older respectively. As has been mentioned, because these measures are cumulative, they allow for effects that persist over time.

It could be argued that events occurring after age 30 are less likely to be the first inter-firm mobility event in the respondent’s life and this might confound the results. Therefore I ran a two part sensitivity test. First I modeled distinguished each type of inter-firm mobility event based on whether it was a first or subsequent event, but did not control for the age at which the event occurred. The only variables for which subsequent events were significant were voluntary changes while remaining in the same occupation and displacement while changing occupation. I therefore added variables indicating if the respondent had experienced a subsequent event for these types of inter-firm mobility to my original model. These variables were not statistically significant and likelihood ratio tests indicated they did not improve the fit of the model, so I dropped them. I also conducted a second sensitivity test where I restricted all inter-firm mobility events regardless of the age at which they occurred to the first event in the respondent’s working life (since age 18 or completing full-time schooling). I ran these models both including variables for subsequent events and excluding them. The results are very similar to the original models. I decided to use the original models as these do allow for multiple effects of inter-firm mobility events that occur far apart in an individual’s life which I believe is appropriate.

For each type of inter-firm mobility event which involves an occupation change, I include a variable measuring the number of years since the event occurred. For involuntary mobility (e.g. displacement, firing and family related changes, for each subsequent event the persons
experiences before or after age 30, I reset the duration clock by the date of that subsequent event. While I am not explicitly modeling the impact of these subsequent events (and exploratory analysis showed their additional effect to be insignificant), it is reasonable to expect that each subsequent event will slow the wage recovery from involuntary job loss. I explored using similar events for the types of inter-firm mobility while remaining in the same occupation, but likelihood ratio tests showed these variables did not improve model fit. This is not surprising, since, as discussed in the literature review, occupation changes require greater adaptation to the new position in terms of learning occupation specific skills, which may mean the effects of voluntary inter-firm mobility are not immediately present. Since the negative effects of involuntary firm change while remaining in the same occupation are negligible anyway, it is logical they would not change with duration since the mobility event.

Exploratory analysis indicated that the impact of duration since the inter-firm mobility event was linear for the various types of involuntary inter-firm with occupation change, but leveled off after three years for voluntary inter-firm mobility with an occupation change. Therefore, for the various types of voluntary inter-firm mobility, I top-coded the years since the event at 326.

I include interactions with having a bachelor’s degree for each type of voluntary inter-firm mobility:

- remaining in the same occupation, event occurred before age 30,
- remaining in the same occupation, event occurred age 30 or older
- change to new non-managerial occupation, event occurred before age 30

26 Separate variables to measure the time since each type of inter-firm mobility were created for events occurring before age 30 and at age 30 and older, and for displacement with a new occupation were created for before age 30, ages 30-39 and age 40 and older.
• change to new non-managerial event occurred age 30 or older
• change to new managerial occupation, event occurred before age 30
• change to new managerial event occurred age 30 or older

I also include interactions with having bachelor’s degree for:
• displacement while changing occupation, event occurred before age 30,
• displacement while changing occupation, event occurred after age 30

There were not enough cases of displacement while changing occupation after age 40 for persons with a B.A. to make distinguishing the interaction term between ages 30-39 and age 40 appropriate. The percentages of persons with a bachelor’s degree who experienced the other types of inter-firm mobility was not large enough to make estimates of interaction terms reliable.

Occupation is measured by three digit Unite States census codes. For 1979-2000, I used the 1970 codes which are available through 2000\(^\text{27}\). For 2002 onward, only the 2000 codes are available for the NLSY79, so I used those. In order to assess changes in occupation between 2000 and 2002, I harmonized both the 1970 and 2000 codes to an aggregated set of census codes based on the 1990 codes. Managerial occupations are defined as those specific occupations described as a manager, supervisor or administrator\(^\text{28}\).

Analysis Technique

I will use random and fixed effects models with robust standard errors. I will run separate models for men and women. Figure 3.2 shows the percent of men and women who have

\(^{27}\) The 1990 codes are not available for the NKLSY79. The 1980 codes are available 1982-2000 but there is a significant amount of missing data.

\(^{28}\) While some of these are listed in the broad ‘Managerial Occupations’ category, others, specifically supervisor positions, are scattered throughout the list (e.g. supervisor in the clerical category, supervisors in the service occupations category)
experienced at least one of the 4 types of firm changes. While some of the percentages are not, given the large sample sizes they generally appear reasonable for detecting effects. The exceptions might be family related mobility for men and firing while remaining in the same occupation for both men and women. Since the literature suggests that family-related inter-firm mobility does not significantly impact men’s wages this is not much of a concern. A limitation is that it is difficult to reliably estimate the impact of firing while remaining in the same occupation.

For both men and women, I will run three sets of models. The first model includes all of the types of inter-firm mobility including interaction terms, and all of the control variables excluding firm and occupational tenure. The second model adds variables for firm and occupational tenure. The third model excludes the firm and occupational tenure variables but for adds the following four variables, each of which measures the fraction female in the individual’s occupation in the year a specific different type of voluntary-inter firm mobility occurred:29

- Fraction female in occupation in year experienced voluntary inter-firm mobility, remaining in the same occupation, before age 30, individual has B.A.
- Fraction female in occupation in year experienced voluntary inter-firm mobility, remaining in the same occupation, at age 30 or older, individual has B.A.
- Fraction female in occupation in year experienced voluntary inter-firm mobility with change to new non-managerial occupation before age 30, individual has B.A.
- Fraction female in occupation in year experienced voluntary inter-firm mobility with change to new non-managerial occupation, at age 30 or older, individual has B.A.

29 For those who change occupations, the fraction female is in the new occupation. I did also explore using a variable for the change in fraction female between the two occupations but this was not statistically significant. If the person with a bachelor’s degree experiences a subsequent change of the same type either before or after age 30, I update the percent female in the occupation to reflect the value for the latest occupation and/or latest year for that occupation. While I am not explicitly modeling these subsequent events, it can be argued to the extent that the context in which the mobility occurred is different for the subsequent event, the more recent context would be most important.
For individuals who have not experienced the specific type of voluntary inter-firm mobility, the respective variable measuring fraction female in the occupation in the year that type of inter-firm mobility is set equal to 0, the same as the variable measuring whether that type of voluntary inter-firm mobility has occurred. This allows us to compare wages among individuals who have experienced a specific type of voluntary inter-firm mobility but into/within occupations with different female representation.

The purpose of these variables is to examine the extent to which gender differences in the impact of voluntary inter-firm mobility are a result of occupational segregation, e.g. the types of occupations men and women are employed in, here measured by the percent female in the individual’s occupation. Thus, I only included these variables for measures of voluntary mobility for which coefficients from Model 1 which showed statistically significantly (p < .05) more positive results for men.

For this same reason, as shown above, I model these four variables as interactions with having a bachelor’s degree. This is because for each of these four measures of voluntary inter-firm mobility, the differences between men and women for the main effects (impact for individuals without a bachelor’s degree) were negligible. It is the interactions with education that showed gender differences. Therefore I wanted to explicitly examine how the female representation in an occupation impacts the relationship between the four measures of voluntary inter-firm mobility and wages for individuals with a bachelor’s degree.\(^\text{30}\) Because most

\(^{30}\) The difference between men and women for bachelor’s degree with change to new non-managerial occupation, event occurred before age 30 is not significant at p < .05, but I included this interaction for the sake of completeness.
individuals in the sample do not have a bachelor’s degree, if I simply included these variables for
the whole sample, the effect would be dominated by the non-bachelor’s degree holders.\footnote{I also
explored including both the main effects and the interaction terms with education for these 4
variables. However, for women, this resulted in high levels of multi-collinearity between the main
effects and respective interaction terms with education, rendering both sets of parameter estimates
unreliable. Incidentally, similar problems also appeared with the indicator variables measuring
whether the individual had ever experienced that type of voluntary inter-firm mobility and the
interactions of those variables with having a bachelor’s degree. Multi-collinearity issues are not
uncommon when a linear main effect as well as interactions between that linear main effect and
another variable are both included in a model. Since the main effects of the variables measuring
percent female in the occupation in the year of inter-firm mobility (impact for persons without a
bachelor’s degree) were not adding anything conceptually, I dropped those variables from the model.}

As has been mentioned, the NLSY79 surveyed respondents every year from 1979-1994 and
every two years from 1994-2012. Therefore it is likely that from 1994-2012, some portion of
inter-firm mobility events are missed.\footnote{In principle the NLSY79 has data on all firms and firm
changes between surveys but there is a large amount of missing data (e.g. close to 80% in some cases),
particularly for occupations, for all jobs other than the current/most recent job held at the survey
date. Therefore I restricted analysis to the current/most recent job in each survey year.} This is not an
issue if the same event occurs twice in a two year period, as my measure captures whether the event
has occurred at least once in the person’s workforce history. However, if two different type of
inter-firm mobility events occur in a two year period, only one will be captured. Inter-firm mobility
events which do not involve an occupation change are more likely to be missed as if the individual
dchanges occupation during either inter-firm mobility event, this will show up in the survey as an
occupation change. The change in survey administration is particularly important as I am comparing
results based on the age at which mobility events occur and more events will potentially be missed in
the later survey years when the data is only available in 2 year intervals.

Using data from 1979-1994, I recalculated the prevalence of each type of inter-firm
mobility, using only data from the even years of the survey and thus restricting the number of
mobility events that can occur in a two year interval to 1. I then compared these results with the
original data from 1979-1994 to estimate the extent that using two year intervals results in
mobility of various types not being captured. These comparisons are shown in Table 3.1. I only do this for the mobility events that occur before age 30 because the overall number of events occurring after age 30 before 1994 is very small due to the age of the sample (29-36 in 1994).

The degree of missing data depends on inter-firm mobility type. Whereas for most types of inter-firm mobility that involve an occupation change approximately 20% of observations have missing events. However, for displacement while meaning in the same occupation about half of the observations have missing events and for voluntary inter-firm mobility nearly all of the events are missing. This is due to the structure of the data – if either inter-firm mobility event in a two year interval involves an occupation change, the person will be recorded as having changed occupations.

However it is important to remember that mobility tends to occur more frequently earlier in an individual’s career. Thus, we are more likely to miss inter-firm mobility events by only including even years from 1979-1994 then will be missed by only having even years from 1994-2012. The overall frequencies of each type of inter-firm mobility event in Figures 2-2 and 2-3 support this. For instance, for both displacement while remaining in the same occupation and voluntary inter-firm mobility while remaining in the same occupation, the percentages of respondents that experience these events before age 30 (almost all of which occur before 1994) and after age 30 (almost all of which occur after 1994) are very similar. If two year intervals from 1994-2012 fail to capture mobility while remaining in the same occupation to the degree that Table 3.1 implies, the patterns in Figure 3.2 and 2-3 would likely reflect this.

I also conducted an additional sensitivity analysis, where I only used the even years in the survey. I also based my calculations of whether and what type of inter-firm mobility event

---

33 If a person is missing a type of mobility event in year 1982, they are also missing it in each subsequent year, unless a second event of the same type occurs in an even year and is thus captured.
has occurred based on the data from the even year surveys only. While some of the coefficients from these models are very similar to the original models, other coefficients differ (e.g. voluntary mobility while remaining in the same occupation) and tend to have unrealistic values in the models using two year intervals from 1979-1994. I ultimately decided to use the complete data set for my analysis because I think it is actually more accurate. Only including even years from 1979-2012 and, thus making the time between surveys consistent, in principle makes the probability of missing inter-firm mobility events independent of time (and hence age), but I do not believe this is the case in practice. This is because, as I have mentioned mobility tends to occur more frequently earlier in an individual’s career. Thus, by only including even years from 1979-1994 we are likely to introduce more bias into the coefficients for mobility occurring before age 30 than the two year intervals after 1994 create for the coefficients for mobility over age 30.

Other than the aforementioned issue of missing years, minimal amounts of data are missing for any variables for the NLSY79 so I use listwise deletion techniques.

Results

Descriptive Statistics

Figure 3.2 and Figure 3.3 show the percentage of respondents who have experienced at least one event of each type of involuntary and voluntary inter-firm mobility respectively. Displacement with a new occupation is by far the most form of involuntary inter-firm mobility. The likelihood of experiencing this event appears to decline significantly with age for men, but not for women. Women are much more likely than men to experience inter-firm mobility for family related reasons. Finally, for all types of involuntary inter-firm mobility, for both age
groups, mobility while changing occupations is more common than remaining in the same occupation at the new firm.

Voluntary inter-firm mobility while changing to a new non-managerial occupation is the second most common form of inter-firm mobility, and this form of mobility also appears to decline with age. Voluntary inter-firm mobility while remaining in the same occupation or changing to a managerial occupation do not appear to change much with age. Finally, there are few gender differences in the prevalence of any type of voluntary inter-firm mobility.

Table 3.2 shows descriptive statistics for the independent variables. We see that the women in the sample have higher educational attainment than the men, with higher rates of completing a high school diploma and at least some college. The women are also more likely to work part time. Work experience is fairly equivalent between the two genders, with men having close to a year more of work experience on average. The women are more likely to work in clerical and service occupations whereas men are more likely to work in craft and operator positions, all of which mirrors national averages. However, women in this sample are more likely to work in professional and technical occupations than men which likely is a result of their higher educational attainment.

Regression Results

Fixed effects regression coefficients for men and women for the various types of mobility, including interaction terms with education, are shown in Tables 3.3 through 3.5. Table 3.3 shows the results from Model 1, the original model. Table 3.4 shows the results from Model 2 which also includes variables for firm and occupational tenure. Table 3.5 shows results from Model 3 which excludes the tenure variables but includes the four interaction terms between
having a bachelor’s degree and the fraction female in the woman’s occupation for women experiencing voluntary inter-firm mobility into a new non-managerial occupation or remaining in the same occupation, for both mobility events that occur before and after age 30.

The results from Tables 3.3 through 3.5 are illustrated by Figures 3.4 through 3.11. In each figure, the bars represent model coefficients and the stars above the bars represent the statistical significance of those bars. Throughout the results section I use the shorthand ‘log wages’ to refer to the outcome, log hourly wage rate adjusted by the CPI.

**Involuntary Job Loss**

Figure 3.4 shows the impact on log wages of displacement in the year of displacement for individuals without a bachelor’s degree. We see from Figure 3.4 that while there is a negative impact on wages of displacement while changing to new occupation, this impact grows steadily with age at older ages of displacement. While displacement at ages younger than age 30 results in a loss of .04 log wages for men and .03 log wages for women, the loss for displacements at ages 40 and over are .17 log wages for men and .10 for women. For both men and women, the impact of displacements that occur before age 30 are statistically significantly different (p < .05) from the impact of displacements that occur at ages over 40. The impact on log wages is significantly worse for men than women at when the displacement occurs at ages 30-39 (p < .1) and ages 40 and over (p < .05).

As with paper 1, the impact of displacement while remaining in the same occupation does not have a significant impact on log wages. Furthermore, there is only scattered evidence of abatement over time of the negative impact of displacement. Model 1 coefficients for the impact

---

34 Displacements occurring between ages 30-39 are significantly different from displacements at ages 40 and older and ages < 30 for men (p < .05) and for women (only at p < .1).
on log wages of the time since displacement are positive but only significant for displacement with a new occupation occurring at ages 30-39 (men) and all ages under 40 (women).

Figure 3.5 compares the coefficients from Model 1 for displacements while changing occupation with the respective coefficients from Model 2, which adds controls for firm tenure and lifetime occupational tenure. For both men and women, at all ages of displacement, controlling for tenure results in a statistically significant abatement in the wage loss due to displacement. The contribution of tenure grows progressively dramatic as the age of displacement increase. For displacements between ages 30-39, loss of tenure accounts for approximately 33% of the wage loss for men and approximately 60% of the wage loss for women. For displacements age 40 and over, loss of tenure accounts for slightly over half of the wage loss for men and approximately 80% of the wage loss for women. While loss of tenure appears to account for a larger portion of the wage loss for women and men, this is related to the fact that women have smaller wage losses than men to begin with; absolute gender differences in the impact of displacement are no different when tenure controls are included.

**Voluntary Inter-Firm Mobility: Age and Duration Since Mobility**

Figure 3.6 shows the impact of various types of voluntary-inter firm mobility on wages, for individuals without a bachelor’s degree. We see that there are visible differences between the impact of voluntary inter-firm mobility while remaining in the same occupation and voluntary inter-firm mobility while changing to a new non-managerial occupation and that these differences vary depending both on the age at which the mobility occurs and the duration of time since the mobility. For both men and women, when voluntary inter-firm mobility occurs before age 30, in the year of mobility, when the individual remains in the same occupation there is
appositive, significant impact of .04 on log wages. In the year of mobility, there is not a
significant impact at the (p < .05) level for voluntary inter-firm mobility when changing to a new
non-managerial occupation. However, after three years, the impact on log wages becomes
positive and statistically significant (.11 for men and .10 for women) and is in fact significantly
greater than for individuals who stayed in the same occupation\(^{35}\).

For voluntary inter-firm mobility that occurs after age 30, the patterns are somewhat
different. For both men and women, voluntary inter-firm mobility after age 30 has a
significantly negative impact in the year of mobility (-.10 for men and -.09 for women) and this
effect remains negative, although significantly less so, 3 years after displacement (-.03 for men
and -.02) for women. By contrast, the impact on log wages of voluntary inter-firm mobility while
remaining in the same occupation is positive, although statistically insignificant\(^{36}\).

For both men and women the impact of voluntary inter-firm mobility while changing to a
new non-managerial occupation is significantly different between mobility that occurs before age
30 and after age 30, both in the year of mobility and three years after (p < .05). However the
impact of voluntary inter-firm mobility while remaining in the same occupation does not change
significantly as a function of age for men or women.

In general patterns for changing to a new managerial occupation mirror that of changing
to a new non-managerial occupation, although changing to a new managerial occupation is
slightly worse for events that occur before age 30 and slightly better for events that occur after
age 30. Due to the large standard error estimates for coefficients for changing to a new

\(^{35}\) Differences between same occupation and new occupation are statistically significant for women in the year of
mobility and three years later and for men three years after the mobility event.

\(^{36}\) Differences between same occupation and new occupation are statistically significant for both men and women in
the year of mobility and three years later.
managerial occupation, the statistical significance of differences as a function of age and with other types of voluntary inter-firm mobility are scattered\textsuperscript{37}. This is likely due in part to the fact that a wide variety of occupations are classified as ‘managerial’.

Figure 3.7 shows the coefficients for voluntary inter-firm mobility from Model 1 for persons without a bachelor’s degree along with the respective coefficients from Model 2, which controls for firm tenure and lifetime occupational tenure. The impacts for those entering a new occupation are in the year of mobility. In all cases, when tenure is controlled for the impact on log wages is statistically significantly more positive or less negative. For voluntary inter-firm mobility with an occupation change that occurs after age 30 the loss of tenure accounts for approximately 75% of the wage loss for men and two-thirds of the wage loss for women.

In addition, for both men and women, the impact of voluntary inter-firm mobility while remaining in the same occupation is positive and significant when tenure is controlled for. Of course, controlling for tenure does represent a hypothetical situation where no loss of tenure occurs so is not exactly realistic. It is also interesting to note that when tenure controls are added the coefficients for duration since the various voluntary inter-firm mobility events abate only slightly.

Figure 3.8 shows the impact of voluntary inter-firm mobility for individuals with a bachelor’s degree. I include this figure for completeness but will discuss more about the role of education in Figure 3.9. The main point for Figure 3.8 is that differences between voluntary

\textsuperscript{37} There are various scattered significant differences between New Managerial Occupation and Same Occupation or New Non-Managerial Occupation: a) In the year of the mobility, Same Occupation is significantly different from New Managerial Occupation for events before and after age 30 for women and before age 30 for men (all $p < .05$) and after age 30 for men ($p < .1$). b) New Non-Managerial Occupation is significantly different from New Managerial Occupation for women for events $< age 30$ in the year of mobility ($p < .05$) and before ($p < .1$) and after ($p < .05$) age 30 for 3 years after the mobility and for men in the year of mobility for events occurring $> age 30$ ($p < .1$). Differences between changing to a new managerial occupation before and after age 30 are significantly different for men but not for women.
inter-firm mobility while changing to a new non-managerial occupation and vs. remaining in the same occupation are much less consistent, outweighed in most cases by the additional positive impact of having a bachelor’s degree\textsuperscript{38}. Also, similar to those without a bachelor’s degree, voluntary inter-firm mobility with a change to a new non-managerial occupation is significantly more positive in terms of wage returns when the mobility occurs before age 30, both in the year of mobility and three years later (p < .05). However for men with a bachelor’s degree, the positive impact of voluntary inter-firm mobility while remaining in the same occupation also decreases significantly with increasing age of mobility.

\textit{Voluntary Inter-Firm Mobility: Gender Differences}

Figure 3.9 shows the impact of voluntary inter-firm mobility in the year of mobility. We can use this figure to explore both the impact of having a bachelor’s degree and how this varies between men and women. The first thing to note, which can also be seen from the coefficients in Table 3.1, is that there are no statistically significant gender differences at the p < .05 level in voluntary inter-firm mobility for individuals without a bachelor’s degree. However, for men, having a bachelor’s degree, significantly (p < .05) increases the wage returns to all types of voluntary inter-firm mobility shown in Figure 3.9.

\begin{footnotesize}
\textsuperscript{38}NOTE: Didn’t bother with including managerial in chart because only ¼ interaction term is sig. Are several sig diffs between nm and so/nr when combine the interaction term with main effects but usually show change to manager is worse (exception is women > 30).
\end{footnotesize}

For both men and women with a BA, in the year of mobility, New Non-Managerial Occupation is only significantly different from Same Occupation (p < .05) for events that occur > age 30. Three years after the switch differences between New Non-Managerial Occupation and Same Occupation are NS for men and are only significant for women when the mobility is before age 30 (p < .05).
The additional wage returns to voluntary inter-firm mobility for men with a bachelor’s degree are dramatic. For instance in the year of mobility for mobility that occurs earlier than age 30, the additional wage returns to voluntary mobility for men with a bachelor’s degree are .17 log wages for men who remain in the same occupation and .13 for men who change to a new non-managerial occupation. In the year of mobility for voluntary mobility that occurs after age 30, the additional wage returns to voluntary mobility for men with a bachelor’s degree are .10 log wages for men who remain in the same occupation and .08 for men who change to a new non-managerial occupation, for whom the impact of mobility is still negative but much less so.

For women, the results are quite different. For women, the only type of voluntary inter-firm mobility for which having a bachelor’s degree significantly (p < .05) increases the wage returns to mobility is voluntary inter-firm mobility with an new non-managerial occupation, when the mobility occurs before age 30. For all other types of voluntary inter-firm there is no additional wage return to mobility for women with a bachelor’s degree. Not surprisingly, as shown on Table 3.3, the interaction terms with having a bachelor’s degree for voluntary inter-firm mobility with a new non-managerial occupation that occurs before age 30, and voluntary inter-firm mobility while remaining in the same occupation that occurs both before and after age 30, are significantly different between men and women. Thus the main gender difference is that in most cases, women do not receive a bachelor’s degree premium in terms of the wage returns to voluntary inter-firm mobility.

As has been discussed, for individuals with a bachelor’s degree, Model 3 includes variables measuring the fraction female in the individual’s occupation in the year they experienced types of voluntary inter-firm mobility shown in Figure 3.9. Because the variable for fraction female in the individual’s occupation only applies to individuals experiencing mobility it
operates similarly to an interaction term between fraction female in the occupation and the experience of mobility. The Model 3 coefficients for voluntary inter-firm mobility shown in Figure 3.9 are thus ‘main effects’ and show the impact of the respective types of voluntary inter-firm mobility if the individual is employed in an occupation where the fraction female = 0. When combined with the respective variables for fraction female in the individual’s occupation when mobility is experienced we can estimated the impact of voluntary inter-firm mobility into or within occupations at varying fractions female. This is done in Figure 3.10.

Before we turn to Figure 3.10, I note that in Model 3, none of the interactions between having a bachelor’s degree and experiencing various types voluntary-inter firm mobility are any longer statistically significant. In addition, none of the variables measuring the fraction female in an individual’s occupation for bachelor’s degree holders who experience voluntary mobility are statistically significant between men and women. This suggests that in principle, the gender differences visible in Figure 3.9 can be entirely explained by the fraction female in the occupations individuals enter or changes firms within.

We see from Figure 3.10 that unlike in Figure 3.9, the wage returns to voluntary inter-firm mobility look quite similar for men and women. The only type of mobility where we see a visible gender difference is voluntary inter-firm mobility age ages under 30 while remaining in the same occupation. While women and men appear to have similar wage returns in occupations with a high percentage of men, gender differences increases along with the fraction of women in the occupation. The gender differences are not statistically significant, largely because the coefficient for how men’s wage returns vary with the fraction of women in their occupation has a high variance. Therefore this estimate may also be unstable. It is likely this is due in part to there being few young men who change firms within occupations that are highly female dominated.
Summary of Key Findings

- The impact of most types of inter-firm mobility worsen with increasing age at which the mobility occurs: positive wage gains abate and wage losses are larger.

- For individuals without a bachelor’s degree, for mobility events that occur before the age of 30, voluntary inter-firm mobility with an occupation change ultimately brings higher wage returns than voluntary inter-firm mobility while remaining in the same occupation.

- For individuals without a bachelor’s degree, for mobility events that occur after the age of 30, voluntary inter-firm mobility with an occupation change results in a wage loss, while voluntary inter-firm mobility while remaining in the same occupation results in no net wage change.

- For individuals without a bachelor’s degree, the wage loss due to voluntary inter-firm mobility with an occupation change that occurs after age 30 is largely due to loss of firm and occupational tenure.

- The wage gains for voluntary inter-firm mobility with an occupation change are not fully realized until three years after the inter-firm mobility event.

- Men receive a bachelor’s degree premium in the wage returns to voluntary inter-firm mobility. Women do not receive the bachelor’s degree premium for most types of voluntary inter-firm mobility.

- The differences between men and women in the bachelor’s degree premium for voluntary inter-firm mobility can be largely explained by occupational segregation.

- Wage losses due to displacement are restricted to displacement that also involves an occupation change.

- For individuals without a bachelor’s degree, when displacement with a new occupation occurs after age 30, wage losses are worse for men than for women.

Discussion and Conclusion

The above findings have several implications. The first is that analysis of the impact of inter-firm mobility on subsequent earnings is incomplete without an examination of whether or not the inter-firm also involves occupation change. We see that the relationship between inter-
firm mobility, occupation change and wages is complex, with effects varying based on both the
duration of time since displacement and the age at which displacement occurs. The fact that
wage returns to changing occupations voluntarily improves with duration since the mobility
event is not surprising as after several years individuals have had time to develop occupation
specific skills.

As has been discussed, individuals without a bachelor’s degree who voluntarily change
firms and simultaneously change occupations after age 30 suffer a wage loss. This wage loss is
largely due to loss of firm and occupational tenure, which is logical given that older workers will
generally have longer firm and occupational tenure at their prior position. These findings
suggests that additional research might focus on the motivations and experiences of workers who
change firm and occupation after age 30. Is imperfect information playing a role here, e.g. did
these workers expect greater wage returns to their mobility than they ultimately received? Or
does this group of workers have primarily non-economic reason for changing firm and
occupation. It should also be noted that this phenomena does not apply exclusively to less well
educated workers. Men and women with a bachelor’s degree who voluntarily change firms and
simultaneously change occupations after age 30 do not lose wages but they do not receive any
wage returns either.

The primary gender difference in the impact of voluntary inter-firm mobility on wages is
that women do not receive the ‘bachelor’s degree premium’ when remaining in the same
occupation, and when changing occupation after age 30. Education is often presented as an
equalizer in terms of the gender wage gap. For instance, over the past 50 years, much of the
decline in gender based occupational segregation has resulted from changing gender composition
of positions that require a bachelor’s degree (England 2010). However, in terms of the wage
returns to inter-firm mobility, it is women with a bachelor’s degree who to not achieve the gains of vis a vis their male counterparts.

As the analysis further showed, the gender differences in the bachelor’s degree premium in wage returns to mobility is largely explained by occupational segregation. Thus it appears that women are more likely to be employed in occupations that allow for less ‘firm-shopping’, that is, using a career strategy where the individual negotiates a higher salary by changing between competing firms that provide similar services. When women with a bachelor’s degree do change occupations, particularly after age 30, they may tend to move to occupations with a similar gender representation, thus limiting their chances for wage returns for mobility. This topic in particular will be explored more in depth in the third dissertation paper.

Nevertheless, the finding that women with a bachelor’s degree experience gender inequality in wage returns to mobility due to occupational segregation, while women without a bachelor’s degree receive the same wage benefits as men is interesting. This is because, as mentioned, occupational segregation itself is higher among individuals without a bachelor’s degree. It may be that although women without a bachelor’s degree are more segregated, the difference between opportunities for wage returns for mobility does not vary as much among their occupations as if does for occupations requiring a college degree. This would not be surprising given that the variation in wages is much higher among occupations requiring a college degree. In essence, these findings highlight the complex nature of how occupational segregation relates to wages inequality.
Table 3.1: Prevalence of Inter-Firm Mobility Using One and Two Year Intervals

<table>
<thead>
<tr>
<th>Type of Mobility</th>
<th>Percent of Observations for whom Type of Mobility has Occurred using Two Year Intervals 1980-1994</th>
<th>Percent with of Observations for whom Type of Mobility has Occurred using One Year Intervals 1979-1994</th>
</tr>
</thead>
<tbody>
<tr>
<td>Displacement, new occupation &lt; age 30</td>
<td>18</td>
<td>24</td>
</tr>
<tr>
<td>Displacement, same occupation &lt; age 30</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>Fired, new occupation &lt; age 30</td>
<td>6</td>
<td>8</td>
</tr>
<tr>
<td>Fired, same occupation &lt; age 30</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Family Reasons, new occupation, &lt; age 30</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>Family Reasons, same occupation, &lt; age 30</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Voluntary, new non-managerial occupation, &lt; age 30</td>
<td>40</td>
<td>52</td>
</tr>
<tr>
<td>Voluntary, new managerial occupation, &lt; age 30</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Voluntary, same occupation, &lt; age 30</td>
<td>2</td>
<td>13</td>
</tr>
</tbody>
</table>
Figure 3.2: Percentage of Respondents with at least One Involuntary Mobility Event by Type

- New Occupation Displaced
- Same Occupation Displaced
- New Occupation Fired
- Same Occupation Fired
- New Occupation Family Reasons
- Same Occupation Family Reasons

- Men, Mobility < age 30
- Men, Mobility >= age 30
- Women, Mobility < age 30
- Women, Mobility >= age 30
Figure 3.3: Percentage of Respondents with at least One Voluntary Mobility Event by Type

- Men, Mobility < age 30
- Men, Mobility >= age 30
- Women, Mobility < age 30
- Women, Mobility >= age 30
### Table 3.2: Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean (Standard Deviation) or Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Men (N=70,523 person-years)</strong></td>
</tr>
<tr>
<td>Black</td>
<td>26% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Latino</td>
<td>18% (N=70,523 person-years)</td>
</tr>
<tr>
<td>White</td>
<td>56% (N=70,523 person-years)</td>
</tr>
<tr>
<td>No High School Diploma</td>
<td>25% (N=70,523 person-years)</td>
</tr>
<tr>
<td>High School Diploma</td>
<td>39% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Some College</td>
<td>18% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Bachelor’s Degree</td>
<td>18% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Age</td>
<td>31.0 (8.7) (N=70,523 person-years)</td>
</tr>
<tr>
<td>Married</td>
<td>47% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Never Been Married</td>
<td>41% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Widowed/Divorced/Separated</td>
<td>12% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Child in the Household</td>
<td>39% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Child under age 5 in the HH</td>
<td>24% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Work Experience (weeks)</td>
<td>562.3 (418.5) (N=70,523 person-years)</td>
</tr>
<tr>
<td>Part Time Worker</td>
<td>11% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Firm Tenure (years)</td>
<td>4.9 (5.3) (N=70,523 person-years)</td>
</tr>
<tr>
<td>Occupation Tenure (years)</td>
<td>3.7 (4.1) (N=70,523 person-years)</td>
</tr>
<tr>
<td>Manager</td>
<td>11% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Professional/Technical</td>
<td>12% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Service</td>
<td>13% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Sales</td>
<td>5% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Clerical</td>
<td>8% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Craft</td>
<td>20% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Operator/Laborer</td>
<td>32% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Industries:</td>
<td></td>
</tr>
<tr>
<td>Agriculture/Mining</td>
<td>4% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Construction</td>
<td>11% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>24% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Wholesale Trade</td>
<td>4% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Retail Trade</td>
<td>15% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Transportation/Warehousing</td>
<td>5% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Utilities</td>
<td>2% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Communications</td>
<td>2% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Finance/Insurance/Real Estate</td>
<td>4% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Business/Repair Services</td>
<td>9% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Education/Health/Social Services</td>
<td>10% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Arts/Entertainment</td>
<td>2% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Personal Services</td>
<td>3% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Public Administration</td>
<td>6% (N=70,523 person-years)</td>
</tr>
<tr>
<td>Percentage Female in Occupation</td>
<td>27.9 (24.5)</td>
</tr>
</tbody>
</table>
Table 3.3: RegressionModels

<table>
<thead>
<tr>
<th>Model 1 Men</th>
<th>Model 1: Women</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Coeff</strong></td>
<td><strong>SE</strong></td>
</tr>
<tr>
<td>New Occupation Displaced &lt; 30</td>
<td>-0.038*** (0.011)</td>
</tr>
<tr>
<td>New Occupation Displaced &lt; 30 * BA</td>
<td>0.124*** (0.035)</td>
</tr>
<tr>
<td>New Occupation Displaced 30-40</td>
<td>-0.091*** (0.013)</td>
</tr>
<tr>
<td>New Occupation Displaced &gt;= 40</td>
<td>-0.172*** (0.020)</td>
</tr>
<tr>
<td>New Occupation Displaced &gt;=30 * BA</td>
<td>0.043 (0.039)</td>
</tr>
<tr>
<td>Same Occupation Displaced &lt; 30</td>
<td>-0.006 (0.019)</td>
</tr>
<tr>
<td>Same Occupation Displaced &gt;= 30</td>
<td>-0.014 (0.021)</td>
</tr>
<tr>
<td>New Occupation Fired &lt; 30</td>
<td>-0.052*** (0.015)</td>
</tr>
<tr>
<td>New Occupation Fired &gt;= 30</td>
<td>-0.096*** (0.020)</td>
</tr>
<tr>
<td>Same Occupation Fired &lt; 30</td>
<td>-0.002 (0.036)</td>
</tr>
<tr>
<td>Same Occupation Fired &gt;= 30</td>
<td>-0.090* (0.045)</td>
</tr>
<tr>
<td>New Occupation Family &lt; 30</td>
<td>-0.051 (0.035)</td>
</tr>
<tr>
<td>New Occupation Family &gt;= 30</td>
<td>-0.144** (0.052)</td>
</tr>
<tr>
<td>Same Occupation Family &lt; 30</td>
<td>-0.145 (0.128)</td>
</tr>
<tr>
<td>Same Occupation Family &gt;= 30</td>
<td>-0.044 (0.056)</td>
</tr>
<tr>
<td>New Managerial Occupation Voluntary &lt; 30</td>
<td>-0.034 (0.032)</td>
</tr>
<tr>
<td>New Managerial Occupation Voluntary &gt;= 30</td>
<td>-0.071 (0.052)</td>
</tr>
<tr>
<td>New Non-Managerial Occupation Voluntary &lt; 30</td>
<td>-0.048+ (0.027)</td>
</tr>
<tr>
<td>New Non-Managerial Occupation Voluntary &gt;30</td>
<td>0.079* (0.038)</td>
</tr>
<tr>
<td>New Managerial Occupation Voluntary &gt;= 30</td>
<td>0.018+ (0.009)</td>
</tr>
<tr>
<td>New Non-Managerial Occupation Voluntary &lt; 30 * BA</td>
<td>0.127*** (0.024)</td>
</tr>
<tr>
<td>New Non-Managerial Occupation Voluntary &gt;= 30</td>
<td>-0.100*** (0.011)</td>
</tr>
<tr>
<td>New Non-Managerial Occupation Voluntary &gt;30 * BA</td>
<td>0.076** (0.025)</td>
</tr>
<tr>
<td>Same Occupation Voluntary &lt; 30</td>
<td>0.040** (0.013)</td>
</tr>
<tr>
<td>Same Occupation Voluntary &gt;30</td>
<td>0.173*** (0.035)</td>
</tr>
<tr>
<td>Same Occupation Voluntary &gt;30 * BA</td>
<td>0.008 (0.014)</td>
</tr>
<tr>
<td>Same Occupation Voluntary &gt;= 30 * BA</td>
<td>0.105** (0.035)</td>
</tr>
<tr>
<td>Same Occupation Voluntary &gt;30</td>
<td>0.001 (0.001)</td>
</tr>
<tr>
<td>Same Occupation Voluntary &gt;= 30</td>
<td>0.004* (0.001)</td>
</tr>
<tr>
<td>New Managerial Occupation Voluntary &gt;30</td>
<td>0.005 (0.004)</td>
</tr>
<tr>
<td>New Managerial Occupation Voluntary &gt;30 * BA</td>
<td>0.003* (0.001)</td>
</tr>
<tr>
<td>New Managerial Occupation Voluntary &gt;= 30</td>
<td>-0.001 (0.002)</td>
</tr>
<tr>
<td>New Managerial Occupation Voluntary &gt;= 30</td>
<td>0.001 (0.002)</td>
</tr>
<tr>
<td>Years Since New Occupation Displaced &gt;= 30</td>
<td>0.004 (0.005)</td>
</tr>
</tbody>
</table>

*p < .05 ** p < .01 *** p < .001 + p < .1
Table 3.4: Regression Models with Tenure Controls

<table>
<thead>
<tr>
<th></th>
<th>Model 2: Men</th>
<th>Model 2: Women</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff</td>
<td>SE</td>
</tr>
<tr>
<td>New Occupation Displaced &lt; 30</td>
<td>-0.022*</td>
<td>(0.011)</td>
</tr>
<tr>
<td>New Occupation Displaced &lt; 30 * BA</td>
<td>0.122***</td>
<td>(0.035)</td>
</tr>
<tr>
<td>New Occupation Displaced 30-40</td>
<td>-0.059***</td>
<td>(0.013)</td>
</tr>
<tr>
<td>New Occupation Displaced &gt;= 40</td>
<td>-0.082***</td>
<td>(0.021)</td>
</tr>
<tr>
<td>New Occupation Displaced &gt;=30 * BA</td>
<td>0.039</td>
<td>(0.040)</td>
</tr>
<tr>
<td>Same Occupation Displaced &lt; 30</td>
<td>-0.001</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Same Occupation Displaced &gt;= 30</td>
<td>0.012</td>
<td>(0.021)</td>
</tr>
<tr>
<td>New Occupation Fired &lt; 30</td>
<td>-0.037*</td>
<td>(0.015)</td>
</tr>
<tr>
<td>New Occupation Fired &gt;= 30</td>
<td>-0.056**</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Same Occupation Fired &lt; 30</td>
<td>0.004</td>
<td>(0.036)</td>
</tr>
<tr>
<td>Same Occupation Fired &gt;= 30</td>
<td>-0.072</td>
<td>(0.044)</td>
</tr>
<tr>
<td>New Occupation Family &lt; 30</td>
<td>-0.044</td>
<td>(0.035)</td>
</tr>
<tr>
<td>New Occupation Family &gt;= 30</td>
<td>-0.112*</td>
<td>(0.052)</td>
</tr>
<tr>
<td>Same Occupation Family &lt; 30</td>
<td>-0.131</td>
<td>(0.124)</td>
</tr>
<tr>
<td>Same Occupation Family &gt;= 30</td>
<td>-0.046</td>
<td>(0.055)</td>
</tr>
<tr>
<td>New Managerial Occupation Voluntary &lt; 30</td>
<td>-0.002</td>
<td>(0.032)</td>
</tr>
<tr>
<td>New Managerial Occupation Voluntary &lt; 30 * BA</td>
<td>-0.081</td>
<td>(0.053)</td>
</tr>
<tr>
<td>New Managerial Occupation Voluntary &gt;= 30</td>
<td>0.025</td>
<td>(0.027)</td>
</tr>
<tr>
<td>New Managerial Occupation Voluntary &gt;=30 * BA</td>
<td>0.080*</td>
<td>(0.039)</td>
</tr>
<tr>
<td>New Non-Managerial Occupation Voluntary &lt; 30</td>
<td>0.042***</td>
<td>(0.009)</td>
</tr>
<tr>
<td>New Non-Managerial Occupation Voluntary &lt; 30 * BA</td>
<td>0.125***</td>
<td>(0.024)</td>
</tr>
<tr>
<td>New Non-Managerial Occupation Voluntary &gt;= 30</td>
<td>-0.032**</td>
<td>(0.012)</td>
</tr>
<tr>
<td>New Non-Managerial Occupation Voluntary &gt;=30 * BA</td>
<td>0.072**</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Same Occupation Voluntary &lt; 30</td>
<td>0.052***</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Same Occupation Voluntary &lt; 30 *BA</td>
<td>0.171***</td>
<td>(0.034)</td>
</tr>
<tr>
<td>Same Occupation Voluntary &gt;= 30</td>
<td>0.044**</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Same Occupation Voluntary &gt;= 30 * BA</td>
<td>0.108**</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Years Since New Non-Managerial Occupation Voluntary &lt; 30</td>
<td>0.031***</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Years Since New Managerial Occupation Voluntary &lt; 30</td>
<td>0.038***</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Years Since New Non-Managerial Occupation Voluntary &gt;= 30</td>
<td>0.020***</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Years Since New Managerial Occupation Voluntary &gt;= 30</td>
<td>0.003</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Years Since New Occupation Displaced &lt; 30</td>
<td>-0.00002</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Years Since New Occupation Displaced &gt;=30-40</td>
<td>0.003+</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Years Since New Occupation Displaced &gt;=40</td>
<td>0.002</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Years Since New Occupation Fired &lt; 30</td>
<td>0.002+</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Years Since New Occupation Fired &gt;= 30</td>
<td>-0.003</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Years Since New Occupation Family &lt; 30</td>
<td>0.001</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Years Since New Occupation Family &gt;= 30</td>
<td>0.002</td>
<td>(0.005)</td>
</tr>
</tbody>
</table>

* p < .05 ** p < .01 *** p < .001 + p < .1
Table 3.5: Regression Models with Occupation Fraction Female

<table>
<thead>
<tr>
<th>Model 3: Men</th>
<th>Model 3: Women</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coeff</td>
<td>SE</td>
</tr>
<tr>
<td>New Occupation Displaced &lt; 30</td>
<td>-0.038*** (0.011)</td>
</tr>
<tr>
<td>New Occupation Displaced &lt; 30 * BA</td>
<td>0.117*** (0.035)</td>
</tr>
<tr>
<td>New Occupation Displaced 30-40</td>
<td>-0.091*** (0.013)</td>
</tr>
<tr>
<td>New Occupation Displaced &gt;= 40</td>
<td>-0.174*** (0.020)</td>
</tr>
<tr>
<td>New Occupation Displaced &gt;=30 * BA</td>
<td>0.043 (0.039)</td>
</tr>
<tr>
<td>Same Occupation Displaced &lt; 30</td>
<td>-0.007 (0.019)</td>
</tr>
<tr>
<td>Same Occupation Displaced &gt;= 30</td>
<td>-0.014 (0.021)</td>
</tr>
<tr>
<td>New Occupation Fired &lt; 30</td>
<td>-0.052*** (0.015)</td>
</tr>
<tr>
<td>New Occupation Fired &gt;= 30</td>
<td>-0.094*** (0.020)</td>
</tr>
<tr>
<td>Same Occupation Fired &lt; 30</td>
<td>-0.001 (0.035)</td>
</tr>
<tr>
<td>Same Occupation Fired &gt;= 30</td>
<td>-0.094* (0.045)</td>
</tr>
<tr>
<td>New Occupation Family &lt; 30</td>
<td>-0.051 (0.035)</td>
</tr>
<tr>
<td>New Occupation Family &gt;= 30</td>
<td>-0.142** (0.052)</td>
</tr>
<tr>
<td>Same Occupation Family &lt; 30</td>
<td>-0.149 (0.129)</td>
</tr>
<tr>
<td>Same Occupation Family &gt;= 30</td>
<td>-0.020 (0.058)</td>
</tr>
<tr>
<td>New Managerial Occupation Voluntary &lt; 30</td>
<td>-0.036 (0.032)</td>
</tr>
<tr>
<td>New Managerial Occupation Voluntary &lt; 30 * BA</td>
<td>-0.065 (0.051)</td>
</tr>
<tr>
<td>New Managerial Occupation Voluntary &gt;= 30</td>
<td>-0.048+ (0.026)</td>
</tr>
<tr>
<td>New Managerial Occupation Voluntary &gt;= 30 * BA</td>
<td>0.077* (0.038)</td>
</tr>
<tr>
<td>New Non-Managerial Occupation Voluntary &lt; 30</td>
<td>0.018+ (0.009)</td>
</tr>
<tr>
<td>New Non-Managerial Occupation Voluntary &lt; 30 * BA</td>
<td>0.173*** (0.037)</td>
</tr>
<tr>
<td>New Non-Managerial Occupation Voluntary &gt;= 30</td>
<td>-0.100*** (0.011)</td>
</tr>
<tr>
<td>New Non-Managerial Occupation Voluntary &gt;= 30 * BA</td>
<td>0.146*** (0.039)</td>
</tr>
<tr>
<td>Same Occupation Voluntary &lt; 30</td>
<td>0.040* (0.013)</td>
</tr>
<tr>
<td>Same Occupation Voluntary &lt; 30 * BA</td>
<td>0.199* (0.079)</td>
</tr>
<tr>
<td>Same Occupation Voluntary &gt;= 30</td>
<td>0.008 (0.014)</td>
</tr>
<tr>
<td>Same Occupation Voluntary &gt;= 30 * BA</td>
<td>0.274*** (0.072)</td>
</tr>
<tr>
<td>Years Since New Non-Managerial Occupation Voluntary &lt; 30</td>
<td>0.033*** (0.003)</td>
</tr>
<tr>
<td>Years Since New Managerial Occupation Voluntary &lt; 30</td>
<td>0.044*** (0.011)</td>
</tr>
<tr>
<td>Years Since New Managerial Occupation Voluntary &gt;= 30</td>
<td>0.023*** (0.004)</td>
</tr>
<tr>
<td>Years Since New Managerial Occupation Voluntary &gt;= 30</td>
<td>0.011 (0.009)</td>
</tr>
<tr>
<td>Years Since New Occupation Displaced &lt; 30</td>
<td>0.001 (0.001)</td>
</tr>
<tr>
<td>Years Since New Occupation Displaced 30-40</td>
<td>0.004* (0.001)</td>
</tr>
<tr>
<td>Years Since New Occupation Displaced &gt;= 40</td>
<td>0.005 (0.004)</td>
</tr>
<tr>
<td>Years Since New Occupation Fired &lt; 30</td>
<td>0.003* (0.001)</td>
</tr>
<tr>
<td>Years Since New Occupation Fired &gt;= 30</td>
<td>-0.001 (0.002)</td>
</tr>
<tr>
<td>Years Since New Occupation Family &lt; 30</td>
<td>0.001 (0.002)</td>
</tr>
<tr>
<td>Years Since New Occupation Family &gt;= 30</td>
<td>0.004 (0.005)</td>
</tr>
<tr>
<td>Fraction Female in Occupation in year experienced</td>
<td>-0.056 (0.158)</td>
</tr>
<tr>
<td>Same Occupation Voluntary $&lt; 30 \times BA$</td>
<td>Fraction Female in Occupation in year experienced</td>
</tr>
<tr>
<td>-----------------------------------------</td>
<td>------------------------------------------------</td>
</tr>
<tr>
<td>Same Occupation Voluntary $\geq 30 \times BA$</td>
<td>Fraction Female in Occupation in year experienced</td>
</tr>
<tr>
<td>New Non-Managerial Occupation Voluntary $&lt; 30 \times BA$</td>
<td>Fraction Female in Occupation in year experienced</td>
</tr>
</tbody>
</table>

* $p < .05$  ** $p < .01$  *** $p < .001$  + $p < .1$
Figure 3.4: Impact of Displacement on Wages in the Year of Displacement

* p < .05; + p < .1

Figure shows Fixed Effects Coefficients from Model 1. Impact for individuals with no bachelor’s degree.
Figure 3.5: Impact of Displacement w/ New Occupation on Wages in Year of Displacement

* p < .05; + p < .1

Figure shows Fixed Effects Coefficients from Models 1 & 2. Impact for individuals with no bachelor’s degree.
Figure 3.6: Impact of Voluntary Inter-Firm Mobility on Wages for Individuals without a BA

- New Occupation, Non-Managerial
- New Occupation, Non-Managerial, after 3 years
- New Occupation, Managerial
- New Occupation, Managerial, after 3 years
- Same Occupation
- Same Occupation, after 3 years

* p < .05; + p < .1

Figure shows Fixed Effects Coefficients from Model 1.
Figure 3.7: Impact of Voluntary Inter-Firm Mobility for Individuals without a BA: Model 2

* p < .05; + p < .1  
Figure shows Fixed Effects Coefficients from Models 1&2. Impact for New Occupation in year of Mobility.
Figure 3.8: Impact of Voluntary Mobility on Log Wages for Individuals with a BA

* p < .05; + p < .1

Fixed Effects Coefficients from Model 1. Effects for persons with B.A. = main effect + interaction term.
Figure 3.9: Impact of Voluntary Firm Mobility on Wages: Gender Differences

* p < .05; + p < .1

Fixed Effects Coefficients from Model 1. New Non-Managerial Occupation in Year of Mobility Effects for persons with B.A. = main effect + interaction term.
Figure 3.10: Impact of Voluntary Firm Mobility for Individuals with a BA: Percent Female

- New Occupation, Non-Managerial, 10% Female
- New Occupation, Non-Managerial, 50% Female
- New Occupation, Non-Managerial, 90% Female
- Same Occupation, Non-Managerial, 10% Female
- Same Occupation, Non-Managerial, 50% Female
- Same Occupation, Non-Managerial, 90% Female

* p < .05; + p < .1

Fixed Effects Coefficients from Model 1. New Non-Managerial Occupation in Year of Mobility Effects for persons with B.A. = main effect + interaction term.

Introduction

This paper will take a different focus, exploring changes over time in women’s mobility between occupations characterized by different levels of gender based segregation. Occupational segregation is a key factor in perpetuating gender inequality, accounting for approximately 25% of the gender wage gap (Blau 2007). Over the past 50 years, and in particular from 1960-1990, occupational segregation by gender has markedly declined (Blau 2013). Women now are almost equally represented in some occupations, particularly in the professions, that were previously heavily dominated by men. A substantial degree of occupational segregation persists however, and fewer inroads have been made into male dominated blue collar occupations (England 2010). Notably, the major declines in occupational segregation occurred from about 1960 until the mid-1990s, since then, depending on the measures used, occupational segregation has declined much more slowly, if barely at all (Blau 2013).

Jacobs (1989) analyzed the extent to which women’s occupational mobility (e.g. changing occupations) between 1967-1977 was related to their ability to move from female dominated occupations to male dominated occupations and vice versa. Strikingly he found almost perfect independence between female representation in the occupation of origin and the occupation of destination. Based on these findings he developed what is termed the ‘revolving door’ theory, which posited that while occupations remain segregated by gender at an aggregate
level, a substantial number of individual women move in and out of male dominated occupations during their career.

Jacobs’ analysis was conducted on data from the time period when occupational segregation was declining most rapidly. This was a period when women were entering male dominated occupations at high rates. In addition, as they integrated previously dominated male occupations for the first time, many forces, including various forms of discrimination, conspired to many women leaving, or being effectively ‘pushed out’, of these male dominated occupations after only a short period of time. These two opposing phenomena contributed to the patterns Jacobs observed.

I hypothesize that Jacobs’ findings were somewhat of a historical anomaly based on the quick rate at which occupational segregation was declining during the time period in question as well as the high rate of occupational segregation at the start of the at the time period. As occupations have become more integrated by gender, and the rate of occupational desegregation by gender has slowed, the labor market likely has also become less fluid. Women who enter female dominated occupations may be more likely to stay there; the same goes for women in male dominated occupations.

In this paper, using longitudinal data from four cohorts of women in the National Longitudinal Surveys of Youth (born 1923-1984). I will examine how mobility from female dominated, male dominated and integrated occupations into male dominated and integrated occupations, female dominated and integrated and female and male dominated occupations respectively has changed from the mid1960s to the present day. Has the revolving door jammed? I will also test Jacobs’ theory that movement between female and male dominated occupations

---

39 There is plenty of anecdotal evidence for occupations such as police officer and factory operators.
does not vary with age. Because much of the occupational desegregation that has occurred is restricted to middle class occupations, which typically require a college education (England 2010), I will explore whether patterns are different depending on education level. Finally, I will examine the extent to which women’s individual characteristics including educational attainment, attachment to the labor force and family responsibilities, as well as macro-economic conditions account for changes that have occurred over time. Because the literature on movement between male and female dominated occupations has tended to neglect the role of macro-economic conditions, I will pay particular attention to the impact of these factors.

Literature Review

Occupational Segregation by Gender

From the 1960s to the present, there has been a marked decline in the extent of occupational segregation by gender in the United States. For instance, using three digit census occupational codes from 1990, the index of dissimilarity developed by Duncan and Duncan was 69 in 1970, 60 in 1980, 54 in 1990, 52 in 2000 and 51 in 2009 (Blau 2013). The index of dissimilarity measures the percent of men or women who would have to change occupations for employed men and women to be equally represented in all occupations (relative to their proportions in the labor force as a whole). As can be seen, more than 80% of the drop in occupation segregation occurred between 1970 and 1990, with the steepest drop occurring during the 1970s. However, most of the decline in occupational segregation has occurred in ‘middle class’ occupations (professional, management and non-retail sales occupations). In 2000, the index of dissimilarity in these occupations was 40 whereas it was 62 among all other occupations (Cotter, Hermsen and Vanneman 2004). Between 1960 and 2000 the index of dissimilarity for
middle class occupations dropped by 24 points, whereas the index of dissimilarity for all other occupation dropped by only 3 points.

**Revolving Door Theory**

Jacobs’s (1989) analysis of data in 1967 and 1977 suggested two seemingly contradictory findings. First, the labor market is characterized by substantial amount of occupational segregation by gender. Second, there is substantial movement of women in and out of female and male dominated occupations. In fact, Jacobs found that if a woman changed occupations between 1967-77, regardless of whether she was employed in a female dominated (> 70% women), integrated (30-70% women) or (male dominated < 30% women) occupation in 1967, she had equal probability of being employed in any of the three categories in 1977\textsuperscript{40}.

In order to reconcile these findings, he developed what is known as the revolving door theory. The revolving door theory suggests that women have access to integrated and male dominated occupations throughout their lives, but that various forces of social control serve to cause a large percentage of women to also leave these occupations (especially male dominated occupations) after a short period of time. The forces of social control are varied and include childhood socialization to gender roles, discrimination in the workplace, lack of family friendly policies, etc. The revolving door theory also posits that time spent working in a female dominated occupation does not hinder women’s chances of eventually being able to enter an integrated or male dominated occupation. In other words, according to the theory, fluidity of movement between the various groups of occupations does not decline with age. This is in

\footnote{40 NOTE: Part of these findings I think are due to misuse of the data. He appears to have used a variable which gave values of previous years to women not employed in 1977. So this is not comparison of any two actual time points and may overestimate mobility.}
contrast to the theory of cumulative disadvantage which suggests that it is harder to women to enter integrated and male dominated occupations as they age.

Applications of the Revolving Door Theory

Since the publication of *Revolving Doors*, several authors have conducted research to test the theory and explore what factors contribute to women’s capability to enter and remain in male dominated and integrated occupations. In addition to testing Jacobs’ theory through exploring the impact of age and prior experience in female dominate occupations on transitions between male and female dominate occupations, researchers have focused on the role that both individual and macro-economic characteristics play in this process. The types of factors examined by researchers stem from two theoretical perspectives to explain occupational segregation by gender, and by implication movement (or lack thereof) between male and female dominated occupations.

The focus on individual characteristics stems from neoclassical economic theories of women’s selection into specific jobs. One aspect of this theory posits that women choose specific jobs (which may be less demanding and pay less well) because these occupations are more flexible and can accommodate time demands related to childrearing and the need to spend time out of the labor force. A second strain in neoclassical theory suggests that women are segregated into specific occupations because they lack the education or work experience required for other occupations (in part perhaps related to time spend out of the labor force for family reasons). Support for neoclassical theories in regards to occupational segregation has been mixed (Sheridan 1997, England 1982). In order to apply the neoclassical perspective to transitions
between female and male dominated occupations, researchers focus on characteristics such as educational attainment, work experience, marital status and children.

A second theoretical perspective focuses on the role that macro-economic conditions may play in explaining occupational segregation. Reskin’s (1990) theory of labor market queues posits that within general education and skill levels required for the position, employers rank men higher than women in the hiring queue. Labor market queues thus serve as a social closure mechanism to restrict access to high paying and high status jobs to select groups of individuals (Tomaskovic-Devey 1993). Women are only able to move into male dominated, high paying high status occupations when the demand for labor exceeds the supply in the occupation, for instance during periods of rapid occupational growth. A somewhat different theoretical orientation that also focuses on macro-economic characteristics focuses on the extent that the economy is characterized by what is termed ‘the demand for female labor’, which captures the extent to which the economy consists of jobs traditionally done by women. While on a national level the demand for female labor has not been associated with occupational segregation since the mid-1960s, a higher demand for female labor has been found to lead to lower rates of occupational segregation in regional economies (Cotter et al 1998; Cotter, Hermsen and Vanneman 2001). Therefore the concentration of occupations traditionally held by women appears to result in increased opportunities for women to enter formerly male dominated jobs. In order to apply the aforementioned theoretical perspectives, researchers can use a variety of measures of macro-economic conditions.

First, I should note that Jacobs’ findings of complete independence between female representation in the initial and subsequent job has not always been reproduced in other samples from approximately the same time period (S. Jacobs 1995; Rosenfeld and Spenner 1992) as well
as one conference paper using later data (Shin 2005). These papers all suggest that female occupations changers who begin in female dominated occupations are more likely than women who began in male dominated occupations to end up in female dominated occupations. The converse is also true.

**Age**: A couple of projects using data from the 1970s-1990s have examined the extent to which movement in and out of female dominated occupations changes as a function of age. Findings have generally suggested that movement in and out of female (or male) dominated occupations do not vary significantly as a function of age (Chan 1999, Sheridan 1997), which could be interpreted as support of the revolving door hypothesis. The problem is that these longitudinal projects do not control for time period and include a limited age range (ages 20-34; Chan 1999) or a limited number of different birth years (< 5; Sheridan 1997). Therefore age is highly correlated with time period in these models. Given the declines in occupational segregation during this period, we might expect that transitions into out of female and heavily female dominated occupations were increasing. Thus the coefficient for age effects of transitions out of female and heavily female dominated occupations may in fact be negative but may be incorporating the positive effect of time period to produce an overall null effect.

**Prior experience in female dominated occupations**: Research suggests finds that prior work experience in female dominated occupations increases transition rates into female dominated occupations and out of male dominated occupations and lowers transition rates out of female dominated occupations (Chan, 1999; Torre, 2014). This lends some support for the cumulative disadvantage hypothesis.

**Time Period.** The only study to model the impact of time was Torre (2014) who included a variable distinguishing the period 1979-1990 with the time period 1990-2006. The variable was
not significant, but as has been mentioned, for cohort studies (Torre’ sample were born 1958-65) that do not control for age, the effect of time period may be confounded by incorporating potentially opposing effects of age and period.

**Education:** Results for the impact of education are somewhat inconsistent but generally suggest that increasing education, in particular having a bachelor’s degree, lowers the likelihood of moving out of male dominated occupations (Rosenfeld and Spenner 1992) and increases the likelihood of moving out of female dominated occupations (Li 1998). The impact of education was not significant in two other papers. However, of these Torre (2014) ran separate models for managerial and professional occupations, effectively limiting the variance of education, and Sheridan (1997) included so many variables for education (college degree, number of years in college, college attendance) that there is likely undiagnosed multicollinearity limiting the significance of the results.

**Marital Status and Children:** The effect of both marital status and having children is inconclusive. While Sheridan (1997) and Torre (2014) found that married women were more likely to transition into female dominated occupations, Rosenfeld and Spenner (1992) and Chan (1999) found no impact of marital status. Having children under 6 years old has been found to both decrease (Chan1999) *and* increase (Rosenfeld and Spenner 1992) the probability that a woman will move into a male dominated occupation. In addition, having children per se had no impact on the various transitions in other papers (Sheridan 1997, Torre 2014), although being a single mother was found to increase both transitions from female to male dominated occupations and vice versa (Sheridan 1997). While each paper used different covariates, slightly different measurements for female and male dominated occupations, and samples from different time periods, there are no particular factors that clearly explain these inconsistencies.
**Work Experience:** Interestingly, taking breaks from the labor force was associated with a greater likelihood of moving out of female dominated occupations in two papers (Kennelly, 2007; Li 1998). It should be noted that one of these papers is a qualitative analysis of workers in one occupation (furniture sales) and the other paper is based on Swiss data, where the respondents may have experienced greater social and policy supports for time out of the labor force. Thus the findings may not be representative of the United States labor force as a whole. Furthermore, for managers and professionals in the United States, breaks from the labor force were associated with a greater likelihood of leaving a male dominated occupation to enter a female dominated occupation (Torre 2014). Work experience (e.g. number of years in the labor force) on the other hand was found both to lower the likelihood of all transitions (Rosenfeld and Spenner 1992) and have no impact on transitions of any kind (Torre 2014). Overall, the findings suggest that the impact of work experience (including work breaks) is contingent on the measurement used, the sample and the variables included in the model. Finally, working part time was consistently associated with lower likelihoods of exiting female dominated and greater likelihood of exiting male dominated occupations (Li 1998, Torre 2014).

**Economic Conditions:** Sheridan (1997) examined the impact of a variety of state level economic conditions. The survey is the Wisconsin Longitudinal Survey, so most of the respondents were living in Wisconsin, where economic conditions do not always mirror the national economy. Sheridan found that many state level measures of economic conditions (based on the state in which the respondent was currently living) had no impact on transition rates between male and female dominated occupations: unemployment rate, percent of the economy in manufacturing, services, white collar occupations and blue collar occupations; percent of the
labor force that is female. Economic growth was associated with a movement from male
dominated occupations into female dominated ones.

**Summary of Mobility between Male and Female Dominated Occupations:**

What we know (or at least have relatively good evidence of):

- Prior work experience in female dominated occupations is associated with increased likelihood of moving into female dominated occupations and out of male dominated occupations and lower likelihood of moving out of female dominated occupations.

- Increased educational attainment is associated with increased likelihood of moving out of a female dominated occupation and decreased likelihood of moving out of a male dominated occupation.

What we don’t know:

- Accurate (unconfounded) estimates of the extent to which mobility in and out of male and female dominated occupations varies by age

- Accurate (unconfounded) estimates of the extent to which mobility in and out of male and female dominated occupations has changed over time since the 1960s

- Whether any time period trends are moderated by educational attainment

- When a national sample is used, do macro-economic factors such as the unemployment rate, economic growth, occupational segregation and industrial and occupational mix of the economy impact transitions in and out of male and female dominated occupations.

What we don’t know because the evidence is inconsistent:

- The relationships between marital status, children and transitions in and out of male and female dominated occupations

- The relationships between work experience, breaks from the workforce and transitions in and out of male and female dominated occupations.

**Research Questions**

This paper will focus on the following research questions:
• How does mobility in and out of male and female dominated occupations vary by age?

• How has mobility in and out of male and female dominated occupations varied by time from the mid-1960s to the present?

• How do the above patterns vary by educational attainment?

• To what extent do individual (e.g. education, family situation, various forms of work experience) and macro-economic factors can explain changes over time in the mobility in and out of male and female dominated occupations?

• Irrespective of changes over time, what is the relationship between macro-economic conditions and mobility in and out of male and female dominated occupations?

Data and Methods

Sample

This paper will use four NLS surveys: NLS Mature Women (5083 women born 1923-37), NLS Young Women (5159 women born 1944-54), NLSY79 (9002 women born 1957-64) and NLS97 (4385 women born 1980-84). The NLS Mature Women and NLS Young Women include data from 1967-2003 (Mature Women) and 1968-2003 (Young Women). Each survey was administered in 22 different years, so the gaps between surveys are either 1 or 2 years, with one three year gap for the Young Women and two three year gaps for the Mature Women. The NLSY79 was administered annually from 1979-1994 and every other year from 1994-2012 and the NLSY97 was administered annually from 1997-2011. Data are available for each year (for at least one survey) between 1967-2012. In addition, data are available for the NLS Mature Women from ages 30-80, for NLS Young Women for age 14-59, for NLSY79 for age 14-55 and for NLS97 for ages 13-31. I will include women aged 23-65. I restrict the lower age range to 23 so

that most women will have completed their formal schooling. I restrict the upper age to 65 historically this has been the formal age of retirement in the United States, although recently this has been changing. The combination of these 4 surveys results in an unusually long and complete body of data, including women born in 38 of the years from 1923-1984, following each woman from 8-18 two year periods.

For the NLSY97, retention rates for women range between 82-93% over the course of the survey, with retention rates over 90% through the fourth round (2000). For the NLSY79 response rates (for living respondents) are above 90% through 1994 and are at least 79% through 2012. For the NLS Young Women and Mature Women the response rates are somewhat lower. For both surveys response rates are at least 80% through 1977 but then by 2003 fall to 59% for the Mature Women and 58% for the Young Women by 2003.

Variables

I use two outcome variables. Both outcome variables are based on a measure of the female representation in the woman’s occupation. For the first measure, following Jacobs (1989), I divide occupations into three categories: male dominated (< 30% female), integrated (30-70% female) and female dominated (> 70% female). I use three digit census occupation codes to identify occupations for all employed women in that year. The data span over nearly 50 years, during which census occupation codes changed several times. I thus use a set of aggregated occupation codes developed by the Department of Labor (Myer and Osborne 2005). These aggregated codes were designed to be as consistent as possible across the 1960-2000 censuses, typically combining into one broader group, occupation codes that were collapsed or expanded between censuses.
In order to assign occupations to the three categories, I use decennial census data from 1960-2000 and American Community Survey data from 2001-2013 to calculate the % female in each occupation for those years. I then use linear extrapolation methods to calculate the % female in each occupation in the intervening years between 1960 and 2000. I explored using the March CPS data set from each year for this purpose, but for less populated occupations the estimates were unreliable.

The second outcome variable measures the change in the female representation of the women’s occupation from over a two year period. This variable has six categories: 1) remained in the same occupation, 2) changed to a new occupation where the percent female was 30-100 percentage points lower than the originating occupation, 3) changed to a new occupation where the percent female was 10-30 percentage points lower than the originating occupation, 4) changed to a new occupation where the percent female was 10 percentage points lower through 10 percentage points higher than the originating occupation, 5) changed to a new occupation where the percent female was 10-30 percentage points higher than the originating occupation, 6) changed to a new occupation where the percent female was 30-100 percentage points higher than the originating occupation.

Each outcome measure has benefits and drawbacks. The first measure allows us to explore patterns of movement into specific sections of the economy as characterized by female representation. However, to a certain extent the definitions of male dominated, female dominated and integrated occupations may be a bit arbitrary. The second measure gets around this issue by examining access to occupations relative to an individual’s own starting point. However, this measure treats the same percentage point change in female representation as equivalent, regardless of the female representation in the originating and subsequent occupation.
The individual level independent variables include age, calendar year, time (measured in decades; with 1967-79 combined), lifetime years in occupation, race/ethnicity (white, black, Latino/other), educational attainment (no high school diploma, high school diploma, some college, bachelor’s degree), marital status (married, divorced/separated/widowed, never been married), whether there is a child under 5 living in the household, whether there is a child aged 5-17 living in the household, years of work experience, and full time vs. part time work.

The variable to assess national economic conditions in the survey year is the United States unemployment rate. I explored using a variety of other measures of economic conditions including: the percent of the labor force that is female, the percent of the labor force working in white collar occupations, and occupational segregation measured by the index of dissimilarity. However, as is illustrated by Appendix Figure A-1, these variables were very highly correlated both with each other and with calendar year (correlations above 95%; in many cases close to 99%). Therefore it is not possible to disentangle the effects of time from many macro-economic measures.

I also use three technical variables related to the percent female in the woman’s occupation. For the first (three category) outcome measure I also include variables for the national percent of the labor force in male dominated and female dominated occupations two years prior. These variables allow us to examine whether changes over time in the movement into male dominated, integrated and female dominated occupations are simply a function of the availability of these respective types of occupations at any given point. For the second (six

---

42 The NLSY Mature Women and Young Women Surveys do not measure Latino ethnicity but have a variable for ‘other race’. The NLSY97 also includes a variable for ‘multiracial’ I explored having multiracial and other race as separate categories but the numbers were so small that I collapsed them with Latino. No survey specifically measures Asian American/Pacific Islander ethnicity.

43 This is not simply a tautology as will become clear in the results section for three reasons. First, the prevalence of male and female dominated occupations is measured two years prior to the outcome variables. Second, as will be
category) outcome measure, I include a variable for the percentage female in the women’s originating occupation (two years prior). This is because the likelihood of moving to a more or less female dominated occupation is limited in part by the percentage female in the occupation of origin. For instance, if one’s originating occupation is 90% female it is not possible to move to an occupation where the female representation is 30-100 percentage points higher. It is partially due to this limitation that I made the categories of 30-100 percentage points more female and 30-100 percentage points less female with wide ranges.

\textit{Analysis Technique}

The primary research questions for this paper are the extent to which movement into and out of female dominated and male dominated occupations have changed since 1967 and change over the life course. Therefore the data will be structured in the following way: For models using the first (three category) outcome measure, I divide the data (person-years) into three longitudinal sub-samples based on whether each woman is in 1) female dominated 2) integrated or 3) male dominated occupation in any given year. Each woman may thus have data in up to three different sub-samples. For each sub sample, I then separately model the probability that two years subsequently the woman has I) not changed occupation, or has changed occupations and is working in a II) male dominated, III) integrated or IV) female dominated occupation. The actual outcome variable thus has 4 categories\textsuperscript{44}. In order to do this I create

\textsuperscript{44} I do not include transitions out of employment as an outcome. (These women are excluded from the sample). However I did run a sensitivity test estimating models including transitions out of employment as a fifth outcome and the results were very similar to the original models. Therefore exclusion of these women does not appear to bias the results.
matched pairs of survey years in each of the 4 NLS Surveys that are two years apart. The baseline year determines which sub-sample the woman will be placed in for that year as well as the values for the independent variables, and the year 2 years later provides the outcome measurement.

The two year matched pairs for each survey are shown in Table 4.1. Because the NLS Young Women and Mature Women samples do not use a constant number of years between surveys, there is not data for every two year interval during the time span in which the surveys were collected. For the NLS Mature Women, there are 12 matched two year pairs. For the NLS Young Women there are 14 matched two year pairs. For the NLSY79 there are 16 matched two year pairs. For NLSY97 there are 4 matched two year pairs.

In order to model the two year probabilities of moving between male dominated, female dominated and integrated occupations, I use three longitudinal multinomial logit models, one for each baseline sample, each using the 4 category outcome: changed occupations and is in 1) male dominated occupation, 2) integrated occupation, or 3) female dominated occupation or 4) has not changed occupations (which is the reference outcome). If a woman’s outcome category is different from her baseline category (e.g. she transitions), then she is moved to a different sample for the next year. For instance, if her baseline category in 1994 is a female dominated occupation, but she transitions to an integrated occupation by 1998, then for 1998 as the baseline year, she will be moved to the integrated occupation baseline sample. If however she transitions back to a female dominated occupation between 2000 and 2002, then for the 2002 as the baseline year, she moves back to the female dominated baseline sample.

The structure of the data for the models for this paper are very similar to three multiple spell, competing risk discrete time hazard models; multinomial logit is the standard method used
to estimate competing risk discrete time hazard models. As in a discrete time hazard model, the time intervals during which exposure to ‘risk’ (e.g. transition) is measured must be identical throughout the data. I use the method of matching two year pairs to ensure that the time interval for a transition probability is always constant. The data are different from a discrete time hazard model in that the time intervals used in the analysis do not cover the entire span of years from the start of the survey. See Table 4.1 for the two year intervals that are included. This is because, as mentioned, for the Mature Women and Young Women surveys, the intervals between survey years vary (between 1-3 years). I cannot simply use a discrete time hazard model, using all years of data, because then the exposure intervals I would be able to measure would not be constant across the data. In addition, for the Mature Women and Young Women, and to a certain extent for the NLSY79 and NLSY97 as well the data between surveys, e.g. times for starting and stopping occupations, marital status, education, etc are often incomplete. Therefore I cannot simply construct intervals using data from years in which surveys were not conducted.45

However, the incomplete coverage of time for the Mature Women and Young Women surveys and missing person-years in all surveys should not be problematic. When a woman is missing a two year interval, she essentially is right censored and then re-enters either her original sub-sample or a different sub-sample depending on if she changed occupations during the missing time intervals. Similarly, for the Mature Women and Young Women Surveys, for years that are not included in the two year intervals, the entire sample is right censored at the end of the last interval before the time gap and then re-enters the data at the beginning of next two year interval captured in the data.

45 In addition, in any survey it may not be valid to make the assumption that a woman who has the same occupation in year t and year t+2 has not transitioned back and forth in the meantime. A limitation of the analysis is that it is based on transition probabilities at specific points and does not capture all possible transitions.
This structuring of the data is an adaptation of the technique developed by Guo (1993) to handle left truncation. When women ‘re-enter’ the sample they are essentially left truncated, as they have already spent some amount of time in their current occupation that is not included in the data. Using this method (where only the intervals for which there is data are used), allowing women to censor and re-enter the samples will not result in biased parameter estimates as long as starting times for each occupation are known. For the intervals in which there is data, the duration is assigned based on these known starting times. For instance, if a woman ‘re-enters’ the sample having spent 3 years in her current occupation, she is assigned a duration of 3 for that year.\textsuperscript{46} As I have mentioned, information on occupations (including starting times) between survey years is not always complete. However, the intervals between surveys are no longer than 3 years, and are only as large as 3 years twice. Thus the adjustment for left truncation when re-entering works, it is just at times based on a not perfectly precise measure of duration.\textsuperscript{47}

One other difference between the models I estimate and standard discrete time hazard models is that my measure of duration in the occupation of origin is the lifetime tenure in the

\textsuperscript{46} As with any missing data, if the assumption of missing at random is violated the parameter estimates will be biased.

\textsuperscript{47} Left truncation also occurs when at the starting time of the survey, some individuals begin already having experienced ‘exposure’. In this case exposure refers to years of experience in an occupation which results in exposure to the possibility of leaving the occupation. This is a sample selection issue – the sample is incomplete because the sample of women at time ‘t’ years since entering the occupation does not include the women in the sample at large who have already left the occupation at some year lower than ‘t’, before the survey began. Since the individuals who transition early likely differ systematically and in unobserved ways from those who transition later, the resulting parameter estimates will be biased. So the issue applies to any woman entering the survey over age 23 who is currently and has been employed for some number of years in any occupation. However, the NLS surveys all provide a variable for the length of time spent in the current/last occupation in the first survey year. With this information, it is possible to estimate a conditional likelihood produces consistent parameter estimates in the presence of left truncation (Guo 1993). As has been discussed, for a discrete time hazard model, this involves having a woman’s first person-year observation be her first year in the sample (rather than the year she entered the occupation). If she begins the survey having spent 10 years in an occupation, the duration for her first year of data is 10 and so forth.
occupation. This will be only different from the immediate tenure/duration in the occupation if
the woman has two spells in the same occupation. If a woman does transition out of a specific
occupation and later returns to that same occupation, the probability of transitioning out of the
occupation a second time will be almost certainly be influenced by the time spent in that
occupation in the initial spell as well as the most recent spell.

For the second (six category) outcome measure, I use the same structure, two year pairs
and modeling technique (longitudinal multinomial logit). The only difference is that the women
are not divided into three samples based on their occupation of origin; all women are included in
the same model.

Because many women have multiple spells (e.g. different starting occupations) in a
specific sub-sample (or overall for the six category outcome), I use robust standard errors to
adjust for clustering of person-spell observations within persons.

**Modeling Strategies**

For each outcome measure, I estimate a series of four models. For the models with the
four category outcome (male dominated, female dominated, integrated, remain in the same
occupation), I estimate the following models. First I estimate a model just using calendar year
and age to get an overall estimate of the changes in transition probabilities over time, net of age
effects. I include the age variable because as the data are based on a compilation of cohort
samples, the representation of ages across years are not identical. That is, age and year are not
independent, although both are exogenous. This is important since research has suggested that
the probability of transitioning out of occupations declines with age.
Because this model does not include variable for the years in the occupation, it essentially treats the hazard of transitioning out of an occupation as a constant function of the years in that occupation. Another way to refer to this is as an exponential hazard duration parameter. Because the probability of transitioning out of an occupation likely declines with the time spent in that occupation, in one sense the estimates for year and in particular, age, are not accurate. However, as mentioned, the primary goal of this initial model is to get an overall picture of how transition probabilities have changed over time. In this sense, time spent in an occupation can be seen as an intervening variable. For instance, women in more recent years have greater attachment to the labor force and likely spend more years in a specific occupation. The years women spend in specific occupations may be one reason why transition probabilities have changed over time. Therefore to get the overall estimate of changes over time, and not the effect net of years spent in specific occupations, I estimate this model excluding the variable for time spent in the original occupation.

The second model adds the variables for percentage of the national labor force in male and female dominated occupations. The third model also includes all the independent variables including the variable for lifetime occupational tenure. The fourth model adds interactions between calendar year and the three variables for educational attainment (bachelor’s degree, no high school diploma and some college). The series of models for the second (six category) outcome are the same except that for the second model the variable for percent female in the originating occupation is added instead of the variables for percentage of the national labor force in male and female dominated occupations. Furthermore, based on the results from Model 3, where there were negligible effects of year once the individual controls were added to the model, I chose not to estimate Model 4 for the six category outcome.
I also explored an alternate strategy: estimating separate models for each cohort. This method proved to be somewhat unwieldy in that there was no direct estimate of time, which had to be indirectly inferred through comparing the effect of age across cohorts. In addition, it proved challenging to estimate how education moderated the effect of time due to multicollinearity issues. Ultimately I decided to focus on the models combining cohorts and estimating effects of time (calendar year) directly.\(^{48}\)

In order to illustrate the magnitude of the effect of key coefficients from Models 1-4, I simulate a series of predicted probabilities of each outcome. These probabilities are simulated by varying the value of a specific variable of interest (e.g. year, unemployment rate, education level)\(^{49}\) while allowing each respondent (person-year) to retain their values on the other covariates. The predicted probability of each outcome is calculated for each respondent (person-year) at various levels of the independent variable of interest. The final predicted probabilities are averages taken across the individual probabilities of each respondent (person-year). These simulated probabilities are shown in a series of figures.

**Additional Modeling Issues**

The longitudinal multinomial logit model can be represented as follows:

\[
\ln\left[\frac{P(Y_{it} = k)}{P(Y_{it} = j)}\right] = X_{it} \beta_k + u_{ik}
\]

where \(Y_{it}\) is the three category outcome variable, \(k\) is the outcome category at baseline, \(j\) is the category outcome 2 or 10 years later (\(j\) may be the same as \(k\)), \(X_{it}\) is a matrix of explanatory

\(^{48}\) Models with a squared term for age created convergence problems. I explored estimating calendar year as a series of dummy variables but there were no obvious non-linear effects.

\(^{49}\) For Model 4 which has interactions between education and year, probabilities are simulated for various education-year combinations.
variables, $\beta_k$ is the outcome specific coefficient and $u_{ik}$ represents time invariant unobserved characteristics that influence the choice of outcome $k$ (Greene 2004 p. 851).

A typical problem with the multinomial logit formulation is an issue referred to as the Independence of Irrelevant Alternatives. The IIA stems from the assumption that net of the observed characteristics in the model, the specific factors which might influence the woman to move into one of the three occupation categories for the first outcome (e.g. male dominated) are independent from the factors which would lead her to decide to move into the other occupation category (e.g. integrated), remain the baseline category (e.g. female dominated) in a new occupation, or remain in the baseline occupation are independent. This is frequently an unreasonable assumption. For instance, I do not model gender socialization through media sources. This unobserved characteristic is likely to impact how the woman sees herself in relation to all four (or six) occupational options.

However, because the data are longitudinal, by treating the person specific time invariant error terms for each outcome category, e.g. $u_{ij}$, $u_{ik}$, $u_{il}$, $u_{im}$ as a vector of random effects ($\mathbf{u}_i$), it is possible to relax the IIA assumption as correlation between the four (or six) choices is modeled via the correlation among the elements of the vector $\mathbf{u}_i$ (Greene 2004 p. 851, Hartzel 2001, Guilkey 2015).

As has been mentioned, for the models using the 4 category outcome the data have a quasi-hazard structure, where a woman who transitions to a different occupational category is subsequently transferred to a different baseline sub-sample. In such models, it could be difficult to get an adequate distribution for $\mathbf{u}_i$, because while the data are technically longitudinal, for each occupational spell we in fact have only one outcome for each person: the amount of time spent in the original occupation and what occupation category they transitioned to (if at all). However,
The data I am using contain multiple occupational spells in each sub-sample. The percentage of
the individuals in the sub-sample with multiple occupational spells are 55%-83% for the female
dominated occupations baseline sample, 53%-78% for the integrated occupation baseline sample
and 25%-59% for the male dominated occupation baseline sample. For the model with the six
category outcome, nearly all women have multiple spells (any woman who has more than one
occupation in her career has multiple spells)

The upper estimate includes respondents who transition out of an occupation and then re-
enter the specific sub-sample in the same occupation later in that career, but do not transition out
again. Because I use a cumulative measure of exposure (e.g. lifetime years in the occupation), I
am not positive such individuals truly have multiple spells for the purpose of accurately
estimating random effects. This is because they only have one measure of ‘time to event’ (the
occupational tenure when the first transition happened) although they do have additional years in
the occupation (with higher tenure and no transition) after the initial transition. It should be noted
that many of the persons who have multiple spells in a specific sun-sample only have at most 2-3
spells.

Another problem that arises in hazard models is the issue of incorrect estimates of
duration dependence due to unobserved heterogeneity. Because the data of this paper are very
similar in structure to a hazard model, these issues apply here. In the presence of unobserved
heterogeneity, typically time invariant unobserved characteristics that impact duration but are
assumed to be uncorrelated with the independent variables, the estimates of the duration
parameter will be biased downward, essentially because the estimates encompass the effect of
the time invariant unobserved characteristics. Unobserved heterogeneity can also can lead to
inconsistent estimates for the other parameters in the model, even if the unobserved
characteristics are not correlated with any of the independent variables, although the direction of any bias is less clear (Van den Berg 2001).

There is a large literature on incorporating the unobserved heterogeneity into the modeling process through random effects, although the extent to which this process works effectively is a matter of debate. Certainly the process is very sensitive to the choice of distribution for the random effects (Heckman and Singer 1984). However, as has been mentioned, the data I will use contain multiple occupational spells, which typically results in more stable estimates when adjusting for unobserved heterogeneity (Wooldridge 2010). The longitudinal multinomial logit model uses random effects (the vector $u_i$) to incorporate unobserved heterogeneity into the modeling process.

In principle, using the random effects multinomial logit model can correct for the IIA and for unobserved heterogeneity. There are a few issues with the particular models I am running however. The first is the fact that as mentioned on the previous page, only a portion of each sub-sample has multiple spells. In principle this is not a problem as the random effect $u_i$ can be identified if at least some observations have multiple spells. However it does mean that the random effects are primarily determined by only a portion of each sub-sample, who cannot be assumed to be representative of the sub-sample as a whole. This is especially true for the sub-sample originating in male dominated occupations. Given that the purpose of using the random effects multinomial logit model is to correct bias in coefficients, the representativeness of the estimated random effects is very important. This issue is compounded by the fact that most of the persons who have multiple spells only have 2-3 spells. My personal experience using

---

50 The individuals with one spell are technically included in the estimation of the random effects, which is not considered problematic (personal communication, David Guilkey), but my sense is they do not contribute much given that it is very difficult to accurately distinguish between the duration dependence and individual specific unobserved heterogeneity for persons with one spell (Wooldridge 2010).
longitudinal methods for nonlinear outcomes suggests that parameter estimates are more stable with higher numbers of observations per person.

An additional issue is that when estimating random effects for nonlinear models, it is preferable to use the discrete factor method which does not assume a distribution for the random effects (Heckman and Singer 1984). However for my models, the discrete factor method resulted in extreme convergence issues. Therefore I was forced to assume multivariate normal distribution of random effects. Some research has suggested that for multiple spell competing risk hazard models (like the ones in this paper) the parameter estimates are robust to assumptions about the distributions of random effects (Guilkey 2015), so using the multivariate distribution for the random effects may not be particularly problematic here. However, I recently discovered that convergence issues in the discrete factor method frequently occur because STATA uses Newton-Raphson as the default maximization procedure; I plan in future revisions to experiment with other maximization options such as Davidson-Fletcher-Powell.

A final issue was compounded by the fact that I was only able to estimate models using 8 quadrature points for samples of women originating in male dominated occupations and 6 quadrature points for samples of women originating in female dominated and integrated occupations. There isn’t a specific consensus in the literature on what a sufficient number of quadrature points would be, but one technique is to start with a lower number of points (e.g. 4) and see if the coefficients change as more quadrature points are added. I did this (starting with 4 quadrature points for all three samples) and found that the differences using 4 vs 6-8 points were very minimal (e.g. differences in the third decimal place; frequently only in the 4th decimal place). This gives me reasonable confidence in my estimates, although it would have been preferable to do an additional comparison using 8 and possibly 12 quadrature points for all
samples. The reason for using a smaller number of quadrature points is that the time necessary to estimate the model increases dramatically with the number of quadrature points used. It would likely take a month to estimate the models in this paper with 8 quadrature points for the sample of women originating in female dominated occupations; using more than 8 quadrature points would take even longer. (These time estimates are using STATA MP2. STATA-SE which is the version used by killdevil and CPC is much slower.) However, if I am able to get the discrete factor method models to converge, this time process will be significantly reduced.

In sum, due to the limitations of the random effects multinomial logit models I was able to estimate, I am not certain these models will actually produce better estimates than the standard multinomial logit model typically used for competing risk hazard models. Therefore I chose to focus on the results from the standard multinomial logit model but to also estimate the random effects multinomial logit model as a sensitivity test, comparing the coefficients with the original models. I did this for the full model without interaction terms (Model 3). As noted earlier, these models take an incredible long time to estimate (e.g. multiple weeks). I had to abandon estimating the random effects model for the six category outcome as this would have taken several months.

**Results**

While this does not come up very much, in this results section I refer to the NLS Mature Women as the ‘Early Cohort’, the NLS Young Women as the ‘Original Cohort’, the NLSY79 as the ‘Middle Cohort’ and the NLSY97 as the ‘Recent Cohort’. These names are designed to be consistent with the first dissertation paper.
Descriptive Statistics

Figure 4.1 and Figure 4.2 illustrate that occupational segregation has declined over the past 50 years. As Figure 4.1 shows From 1960-2010, the national average percentage female in women’s occupations declined from 71% to 65% and the national median percentage female declined from 81% to 69%. Figure 4.2 shows that the percentage of women in female dominated occupations (more than 70% female) declined from 68% to 49% between 1970 and 2010. During that same time period the percentage of women in integrated occupations (30-70%) female increased from 25% to 42%. Interestingly, the percentage of women in male dominated occupations stayed fairly constant between 1960 and 2010; fluctuating around 10%. This is likely due to the fact that as women entered previously male dominated occupations, these occupations actually became integrated occupations.

This notion is supported by Figure 4.3 which shows that the percentage of the labor force in male dominated occupations declined from 45% to 31% between 1960 and 2010. Over that same period the percentage of the labor force in integrated occupations increased from 30-41%. Part of these trends are also due to the fact that the percentage of the labor force which is female increased during the time (36% in 1967 to 47% in 2012 as shown in Figure A-1). However the percentage of the labor force in female dominated occupations stayed pretty constant from 1960 to 2010; only increasing from 25-28%. Thus not only are women a higher percentage of the labor force, they are also working in more gender integrated positions. The aforementioned results have been substantiated many other articles, they are simply useful to review as background picture here.
Figures A.2 through A.4 in the Appendix Tables and Charts show the transition percentages into by year into male dominated, integrated and female dominated occupations for individuals who were in male dominated (Figure A.2), integrated (A.3) and female dominated (A.4) occupations two years prior. Figure A.5 shows the transition percentages for the six category outcome variable. Because certain age groups are more heavily represented in specific years, these figures are not particularly useful.

More useful are Figures A.6 through A.21 which show the same set of transition percentages by age, shown separately for each of the 4 cohorts. We see from Figures A.6 through A.17 that the transition percentages from all three categories (male dominated, female dominated, and integrated) occupations into each of the three categories declines with age. The strongest declines with age are seen for the original and middle cohorts. Declines with age are slightly flatter for the recent cohort, however this is likely in part due to the fact that data are only available through age 33 for this cohort. For the early cohort, transitions decline only slightly (with a lot of fluctuation) as a function of age. There are no obvious non-linear patterns in the data.

Figures A.18 through A.21 show results for using the six category outcome. Here we again see that for all types of transitions, percentages decline as a function of age, with steeper declines for the original, middle and recent cohorts and a flatter slope for the early cohort. One interesting thing is that for the original cohort, declines as a function of age do not start until about age 34.

Figures A.22 through A.25 show transition percentages as a function of years spent in the occupation for both the four category and six category outcomes. The general pattern here is that all types of transitions decline with additional years spent in the occupation in an approximately
linear fashion. This suggests that modeling years spent in the occupation as a linear variable will be appropriate.

Table 4.2 shows descriptive statistics for the individual level independent variables for the 96,673 person-years in the sample. Slightly more than half of the women are white. All levels of education well represented although the modal group is women with a high school diploma and no college. Nearly 69% of the women are married although approximately half do not have a child in the home. This is due to the fact that the sample includes a wide range of ages, including women at ages before, during and after child-rearing. Nearly 75% of the women are working full-time and the average years of work experience is just over 10 years which is in accordance with the average sample age of 36 years. The average occupational tenure is 4.9 years. Years of work experience and occupational tenure all have large standard deviations which reflects the wide variation in ages in the sample.

**Regression Results: Six Category Outcome**

Table 4.3 shows the regression coefficients for the six category outcome, which models the probability of five transitions defined by the change in the fraction female in the woman’s occupation relative to the reference category of remaining in the same occupation. For both Model 1, which includes variables for calendar year and age and Model 2 which adds a variable for fraction female in the woman’s occupation, the log odds of all transitions significantly decline with both age and calendar year. In other words, over the past 50 years, women have become progressively less likely to switch occupations.

Changes in the predicted probability of each type of transition over time (calendar year) are illustrated in Figure 4.4. Based on coefficients from Model 1, we see that the largest declines over time are in the predicted probability of changing to an occupation that is substantially less
female (category 1: 30-100 percentage points less female). The predicted probability of this transition declines from 10% to 6% from 1970-2010. The second largest decline is the probability of changing to an occupation that has close to the same female representation as the original occupation (category 3: 10 percentage points less to 10 percentage points more female). The predicted probability of this transition declines from 14% in 1970 to 11% in 2010. The third largest decline is in the predicted probability of changing to an occupation that is substantially more female (category 5: 30-100 percentage points more female), which declines from 8% to 6%. The difference between category 1 with category 3 and 5 in the change in predicted probabilities over time are statistically significant. So loosely, we can say that occupational changes in 2010 are less likely to involve movement to a more male dominated occupation than 1970 but the magnitude of the differences is not very large.

The predicted probabilities from Model 2, which adds a variable for the percentage female in the originating (2 years prior) occupation tell a slightly different story. Here the largest declines from 1970 to 2010 are in occupational transitions to an occupation that is more female dominated. The predicted probability of transitions to category 5: 30-100 percentage points more female declines from 9% to 6% and the predicted probability of transitions to category 4: 10-30 percentage points more female declines from 10% to 7%. The predicted probability of transitioning to category 1: 30-100 percentage points less female now only declines from 9% to 7%. This suggests that the reason fewer changes involve a transition to a more male dominated occupation over time may be a function of the fact that women are originating from occupations that have a higher percentage of men to begin with. Because this measure does not disaggregate based on where along the distribution of female representation the women’s original and subsequent occupation fall, it is a bit difficult to interpret the results.
Model 3 adds the variables for individual level characteristics and the national unemployment rate. We see from Table 4.3 that the coefficients for calendar year for the outcomes of 30-100 percentage points more female, 10-30 percentage points less female, and 30-100 percentage points less female are no longer statistically significant. In addition, Figure 4.4 illustrates that for Model 3, there is little visible change in the predicted probability of any outcome as a function of calendar year. This suggests that nearly all of the changes over time can be explained by changes in individual characteristics. (Given that the unemployment rate is cyclical, and changes over time are fairly linear, it is unlikely to contribute much to changes over time).

Regression Results: Four Category Outcome

Calendar Year: The regression coefficients models estimating transitions to male dominated, integrated and female dominated occupations are presented in Table 4.4 (for those originating in a male dominated occupation two years prior), Table 4.5 (for those originating in an integrated occupation two years prior) and Table 4.6 (for those originating in a female dominated occupation two years prior). In Models 1-4, the probability of transitions to all three types of occupations (male dominated, integrated and female dominated) decline statistically significantly with age and calendar year for women originating in all three types of occupations. The one exception is that for women originating in a female dominated occupation, the

---

51 It is also worth noting that Jacob’s finding that the probability of transitioning to a specific type of occupation is the same whatever type the woman originated in is not replicated. Women in female dominated occupations are the most likely to transition into female dominated occupations, women in male dominated occupations are the most likely to transition into male dominated occupations and women in integrated occupations are the most likely to transition into integrated occupations. This is true in all years. Jacobs did look at 10 year transition probabilities but I think the main issue (based on some supplemental analysis I did) is that he used the incorrect variable by mistake. As Revolving Doors is 30 years old this is not an important issue to stress,
probability of transitioning to an integrated occupation does not change significantly as a function of calendar year in Model 1.

The relationship between calendar year and predicted probabilities of transitions using coefficients from Model 1 are illustrated in Figure 4.5. The first thing to note is that as we found using the six category outcome, the predicted probability of transitioning out of one’s current occupation into any occupational category declines with calendar year. The change over time is particularly dramatic for women originating in male dominated occupations. In 1970 the predicted probability of remaining in that same occupation two years later was .42; by 2010 this had increased to .59. Smaller but still substantial effects are found for women originating in integrated occupations who had a predicted probability of .47 of remaining in the same occupation in 1970 which increased to .57 by 2010. For women originating in female dominated occupations the predicted probability of remaining in that occupation two years later increased from .53 to .63 from 1970-2010.

Interestingly, for women originating in female dominated occupations, the predicted probability of exiting the entire set of female dominated occupations has stayed constant from 1970-2010 at just less than .2. While the predicted probability of transitioning to a male dominated occupation does drop (from .06 to .03) this is offset by a (not statistically significant) increase in the predicted probability of transitioning to an integrated occupation. Thus the drop in the predicted probability of leaving the woman’s specific occupation is fully accounted for by a corresponding drop in the predicted probability of transitioning to another female dominated occupation. For women originating in a male dominated occupation the patterns are somewhat different. The predicted probability of transitioning from a male dominated to a female dominated occupation in 2010 is less than half of that in 1970 (.25 in 1970 vs. .12 in 2010). The
predicted probability of transitioning from a male dominated to an integrated occupation falls only slightly during this time (.22 in 1970 to .21 in 2010).

Finally, regardless of the occupation type of origin, the predicted probability of transitioning into both new male dominated occupations and new female dominated occupations has visibly declined; whereas changes in the predicted probabilities of transitioning into new integrated occupations are minimal. In particular the impact of calendar year on the predicted probabilities of transitioning into a female dominated occupation are statistically significantly different from the impact of calendar year on the predicted probabilities of transitioning into a new male dominated or integrated occupation; this is true regardless of the occupation type of origin. This may be related to the fact that female dominated occupations consist of a much smaller share and integrated occupations consist of a much greater share of the labor force in 2010 than 1970 (see Figure 4.2).

**Calendar Year Net of Occupational Distribution:** To explore the extent to which the predicted probabilities of transitions into specific occupation types are a function of the share of the national labor market in male dominated and female dominated occupations, Model 2 adds variables for the percent of the labor force in male dominated and female dominated occupations two years prior. The intent of this model was to control for the potential impact on transition probabilities of the extent of the availability of specific types of occupations. If more individuals are transitioning into integrated occupations because these occupations make up a greater share of the labor market this is not particularly interesting. Note however that this is not a forgone conclusion. For instance it might be that a high proportion of the labor market is in integrated occupations but individuals tend to remain in these occupations for a long time whereas there is more churning within or between male dominated and female dominated occupations.
The relationship between calendar year and predicted transition probabilities using coefficients from Model 2 are shown in Figure 4.6. What is immediately apparent from comparing Figure 4.6 with the illustration of Model 1 coefficients in Figure 4.5 is that when variables for the share of the national labor market in male dominated and female dominated occupations are included, the relationship between calendar year and the probability of remaining in the same occupation changes. Whether the woman originates in a male dominated, female dominated or integrated occupations, her predicted probability of remaining in that same occupation is lower in 1970 and higher in 2010, compared to Model 1 which does not control for the share of the labor market in male and female dominated occupations. This suggests that in addition to controlling for the direct impact of the availability of specific types of occupations these variables also capture more complex contextual factors. In other words, the question arises why does the relative availability of different types of occupations impact the overall probability of an occupational transition per se rather than a transition to an occupation in one of the specific three categories relative to the others?

To explore this further, we note that Tables 4.4 through 4.6 show that no matter what type of occupation the woman originates in, an increase in the share of the labor market that is female dominated and an increase in the share of the labor market that is in female dominated occupations are both associated with a decrease in the likelihood of transitioning into any of the three types of occupations. The only exception is that neither variable influences (at the p < .05 level) the transition from male dominated to female dominated occupations or vice versa. In other words, when the labor market consists of more integrated occupations, conditions are more conducive to women transitioning both into and out of integrated occupations as well as into a new specific occupation within the same category (male dominated, female dominated,
integrated) as their original occupation. This seems to capture some sort of broader cultural relationship between occupational mobility in general and the presence of integrated occupations, e.g. when more occupations are integrated perhaps women feel and/or are more accepted in the labor market in general and this is associated with an increase in occupational mobility.

Figure 4.6 also illustrates that net of the share of the different occupation types in the economy, the predicted probability of a woman transitioning out of the entire set of female dominated occupations has in fact declined markedly over time (.26 in 1970 to .12 in 2010). The predicted probability of a woman transitioning out of the entire set of male dominated occupations has also decreased markedly over time (.54 in 1970 to .31 in 2010). While the predicted probability of transitioning from a male dominated to a female dominated occupation is very similar to Model 1, the probability of transitioning from a male dominated to an integrated occupation also declines substantially (.31 to .14).

Another interesting finding illustrated by Figure 4.6 is that net of the share of the different occupation types in the economy, the declines over time in transitions out of male and female dominated occupations are mainly driven by declines in the overall probability of changing occupations at all. As Figure 4.6 shows, the largest proportionate decline, as well as the largest decline in terms of percentage point difference, from 1970-2010 or women originating in a male dominated occupation is the predicted probability of transitioning to another male dominated occupation; the largest proportionate decline for women as well as the largest decline in terms of percentage point difference, for women originating in a female dominated occupation is transition to another female dominated occupation. This is a somewhat different result from Figure 4.5, where the largest proportionate decline for transitions out of male dominated
occupations was into female dominated occupations and vice versa, although the largest declines in terms of percentage point differences are in transitions to a female dominated occupation regardless of occupation type of origin.

**Role of Individual Characteristics:** Figures 4.7 to 4.9 compare changes over time in the predicted probabilities of the various transitions between Models 1 and 2 and Model 3, where individual characteristics and the unemployment rate is controlled for. For women originating in male dominated occupations, nearly all of the decline over time in transition to female dominated occupations appears to be due to individual characteristics (the change from 1970-2010 is .22 to .12 in Model 2 vs .17 to .16 in Model 3). The individual characteristic which is likely important here is having a bachelor’s degree. As shown in Table 4.4, having a bachelor’s degree decreases the likelihood of transitioning from a male dominated to a female dominated occupation and the percentage of women with a bachelor’s degree has increased over time, which would explain some of the decline in transitions from male to female dominated occupations.

For women originating in integrated occupations, most of the decline over time in the predicted probability of transitioning into a male dominated occupation appears to be related to individual characteristics (the change from 1970 to 2010 is .17 to .5 in Model 2 and .08 to .04 in Model 3). The characteristic that is likely important here is education level. As shown in Table 4.5, contrary to what we might expect, having higher education decreases the likelihood of transitioning from an integrated to a male dominated occupation and lack of a high school diploma increases this likelihood. As education levels have increased over time, this would explain the drop in the predictive probability of transitioning from an integrated to a male dominated occupation. It should be noted that because Model 3 does not include interactions between education and year, the results do not fully account for the complex relationships.
between these variables. For instance, having a bachelor’s degree might actually have increased
the likelihood of transitioning from an integrated occupation to a male dominated occupation in
1970 before the professions were integrated but this would cease to be the case as the professions
became integrated. Therefore the findings presented in this paragraph are not necessarily
particularly useful; the informative findings will be discussed when Model 4 results are
presented.

Finally, for women originating in female dominated occupations, individual
characteristics appear to play only a minimal role in the changes in occupational transitions over
time.

**Interactions between Education and Time**: Tables 4.4 through 4.6 show that there is
a significant interaction between having a bachelor’s degree and calendar year on the likelihood
of transitioning from a male dominated occupation to a new male dominated, female dominated
or integrated occupation, on the likelihood of transitioning from an integrated occupation to a
male dominated occupation and on the likelihood of transitioning from a female dominated
occupation to a new female dominated or integrated occupation. There is also a significant
interaction between having no high school diploma and calendar year on the likelihood of
transitioning from a male dominated occupation to a new male dominated or female dominated
occupation, on the likelihood of transitioning from an integrated occupation to a male dominated
or female dominated occupation, and on the likelihood of transitioning from a female dominated
occupation to an integrated or new female dominated occupation.

Figure 4.10 illustrates the predicted probabilities of occupational transitions for women
originating in a male dominated occupation. Recall that coefficients from Model 3 indicated that

---

52 The interactions between bachelor’s degree, some college and no high school diploma and calendar year are
centered around 1967 so that the main effect of each type of education is the effect in 1967.
there was no change over time in the predicted probability of transitioning from a male dominated to a female dominated occupation. However this null effect actually masks significant variation between educational groups. We see that from 1970-2010 the predicted probability of transitioning from a male dominated to a female dominated occupation fell from .2 to .15 for individuals with a high school diploma. However for individuals with a bachelor’s degree the predicted probability rose from .11 to .15 and for individuals with no high school diploma the predicted probability rose from .13 to .18. From 1970 to 2010, the predicted probability of transitioning out of the set of male dominated occupations fell from .49 to .33 for those with no high school diploma and from .48 to .29 for those with a high school diploma but only from .38 to .32 for those with a bachelor’s degree. Much of the differences here are related to the values in 1970, when women with a bachelor’s degree had a lower likelihood of transitioning out of male dominated occupations; by 2010 the predicted probabilities for the three educational groups are much closer.

Figure 4.11 and 4.12 illustrate the predicted probabilities of occupational transitions for women originating in an integrated occupation and female dominated occupation respectively. One notable difference across educational groups is that in 1970, women with both bachelor’s degrees (.31) and those with no high school diplomas (.31) had higher probabilities of transitioning out of the set of female dominated occupations than women with a high school diploma (.21). However, by 2010 transition probabilities overall had converged across education groups (between .12-.15 for all groups). In addition, contrary to what we might have expected, consistently across years, women with a bachelor’s degree have the lowest predicted probability of transitioning into male dominated occupations from either female dominated or integrated occupations.
Interestingly the levels and changes over time in the overall predicted probabilities of switching occupation do not differ that much between education groups. From 1970-2010, the predicted probability of staying in the same occupation rose from .43 to .71 for individuals with no high school diploma, from .41 to .72 for individuals with a high school diploma and from .48 to .73 for individuals with a bachelor’s degree. However individuals with a high school diploma see a much greater drop in the likelihood of transitioning into other female dominated occupations.

**Unemployment Rate:** Tables 4.2 through 4.4 indicate that an increase in the unemployment rate is associated with a statistically significant increase in the transition from a male dominated to an integrated occupation; from an integrated occupation to a new integrated or female dominated occupation, and from a female dominated to an integrated or new female dominated occupation. Figure 4.13 illustrates that for women originating in male dominated occupations, when the unemployment rate is 4.0, the predicted probability of transitioning into an integrated occupation is .20; this increases to .25 when the unemployment rate is 10.0. The predicted probability of transitioning into a female dominated occupation barely changes (an insignificant decline from .18 to .17). Thus a higher unemployment rate is associated with women leaving male dominated occupations. This does not merely reflect overall mobility related to a higher unemployment rate as the probability of moving from one male dominated occupation to another remains constant. However none of the models indicate a significant relationship between the unemployment rate and women’s ability to transition into a male dominated occupation.

Figure 4.13 also illustrates that as the unemployment rate increases from 4.0 to 10.0 the predicted probability of a woman exiting an integrated occupation for a female dominated
occupation increases from .18 to .20. However the predicted probability of a woman exiting a female dominated occupation for an integrated occupation also increases from .13 to .17. Higher unemployment rates clearly are associated with increased movement within and between female dominated and integrated occupations but there is no evidence that women have less access to more integrated occupations in periods of high unemployment.

Summary of Key Findings

- The two-year probability of changing occupations declined markedly for women between 1970-2010.

- The largest declines are in the two-year probability of transitioning out of the set of male dominated occupations, to both female dominated occupations as well as integrated occupations (net of changes in relative size of the occupational categories).
  - However, in 2010, women are still more likely to transition out of the set of male dominated occupations than out of the set of female dominated occupations.

- Overall, the two year-probability of transitioning out of female dominated occupations does not change over time. However, net of changes in relative size of the occupational categories, the two-year probability of transitioning from female dominated to integrated occupations gets substantially smaller over time.

- Once changes in relative size of the occupational categories are accounted for, the declines in transition probabilities of exiting male and female dominated occupations are driven primarily by the fact that women are much less likely to change occupations by 2010.

- A higher proportion of gender-integrated occupations is associated with more occupational mobility for women both into, out of and within gender integrated occupations.

- Whereas the two-year probability of transitioning from male dominated to female dominated occupations declines for women with a high school diploma, it actually increases for women with no high school diploma or a bachelor’s degree.

- The changing patterns over time for different educational groups actually result in a convergence across educational groups by 2010 in most two-year transition probabilities.
Across years, women with bachelor’s degree consistently have the lowest probability of transitioning into the set of male dominated occupations.

A higher unemployment rate is associated with a higher probability of women leaving male dominated occupations but does not appear to impact the probability of entering male dominated occupations.

Discussion and Conclusion

The above key findings have several implications. First, in a general sense, women are cycling less between male dominated, integrated and female dominated jobs. However, the main factor behind this is that women are less likely to switch occupations in general. In other words, the changes over time predominantly reflect greater attachment of women to the labor force rather than changes in access to specific types of occupations or lack thereof. The fact that the unemployment rate is not associated with access to male dominated jobs does not support the existence of gender labor market queues, although the national unemployment rate is a very broad measure of labor demand and may not be sensitive enough to capture men and women’s likelihood of being hired for traditionally male dominated positions. The fact that a higher unemployment rate is associated with an increase in the probability of exit from male dominated positions suggests that it is possible that women may be among the first to be displaced when layoffs occur in male dominated positions. This would be an interesting question to pursue.

The trend in women having more stable, long-term careers in specific occupations is counter-balanced by another trend, an increase the share of the labor force who are employed in integrated occupations which occurred between 1970 and 1990 (and has remained relatively flat since). As we have seen, a greater share of the workforce being employed in gender integrated occupations is associated with higher occupational mobility for women in general. It would be reasonable to expect that occupational integration by gender goes somewhat hand in hand with
more equal treatment of women in the workplace on an individual level as well as access to a
greater share of occupations by women (e.g. in the sense that employers are willing to hire them,
male coworkers accept them etc). In the second dissertation paper, I found that college educated
women did not receive the wage premium to occupational mobility that college educated men do
and that this was almost entirely due to occupational segregation. Thus it is reasonable to expect
that the greater share of the labor force in integrated occupations, the more equal the wage
premium to occupational mobility between women and men and the more women who will feel
occupational mobility is beneficial and will pursue such opportunities.

The fact that the probability of exiting a male dominated occupation for a female
dominated occupations actually increases over time for both individuals without a high school
diploma and individuals with a bachelor’s degree raises some interesting questions. Does this
indicate occupational re-segregation in some form? It would be useful to explore what specific
occupations contribute to this trend. For instance, what constitutes a ‘male dominated’
occupation in 1970 is not the same set of occupations as in 2010. It is possible that the
occupations that remain male dominated in 2010 are particularly difficult for women to remain in
long term for any number of reasons. It is also interesting that this trend applies both to highly
educated and the least well educated women but not women with middle levels of education,
which again indicates that it applies to specific occupational sections in the labor market. Upper
level management and construction work are two occupations which spring to mind.

While there are several differences across educational groups in how the probability of
various occupation transitions has changed over time, these differences as a function of time
nearly all result in convergence of transitions probabilities among education groups in 2010
whereas the transition probabilities differed between the education groups in 1970. If current
time trends for each educational group, the educational groups will eventually diverge again — but in the opposite direction as from 1970. It will be interesting to see if these trends continue, or if probabilities of occupational transitions remain similar across educational groups from this point on.

Finally, related to educational differences, while much of the occupational integration over the past 50 years has occurred in occupations which require a bachelor’s degree, women with a bachelor’s degree consistently have the lowest probability of transitioning into male dominated occupations. This finding is not surprising in 2010, as many of the professions have already become ‘integrated occupations’ and the occupations that remain male dominated may be unwelcoming to women and/or not appeal to women’s preferences. Lack of support of work-family needs likely plays a role here. However, we might have expected that in the 1970s and 1980s women with a bachelor’s degree would have a higher probability of transitioning into male dominated occupations as the professions became integrated. These findings suggest that the integration of male dominated occupations has occurred due to young women of later generations beginning and continuing their careers in male dominated occupations rather than mid-career transitions of women across generations into these occupations.

Addendum to Chapter 3: Random Effects Models

Table 4.10 compares ratios of three sets of coefficients from the original Model 3 for each sub-sample (from Tables 3-4 through 3-6) and the random effects versions of Model 3 for each sub-sample (from Tables 3-7 through 3-9). I compare ratios of coefficients because the coefficients in the random effects models and original models are scaled differently, thus making direct comparisons of coefficients not meaningful. I focus on three ratios between key
coefficients: bachelor’s degree to no high school diploma; unemployment rate to percent of labor force in female dominated occupations and year to age. I include these specific ratios because they include coefficients of conceptual interest and also because the unit of measurement of the independent variables used in each ratio is the same or similar, thus the magnitude of the ratios are less likely to be extremely high or low, which facilitates comparisons.

For the ratio of unemployment rate to percent of the labor force in female dominated occupations, the coefficients are very similar for all sub-samples, for coefficients for each outcome. For ratios of year to age, the random effects models have slightly lower values than the original models, for all coefficients, for all sub-samples. However the pattern is consistent across outcomes and sub-samples. This suggests that the original models may slightly over-estimate the effect of year or underestimate the effect of age, or both. The bias in the ratio is in the range of 5-14%, which is significant although not enormous.

The differences between the two models are most pronounced for the ratio of bachelor’s degree to no high school diploma. A majority of the ratios are very similar between the random effects and original models (differences < 5-7%). However, four notable differences are the log odds of moving from an integrated occupation to another integrated occupation, the log odds of moving from a female dominated occupation to an integrated occupation, the log odds of moving from a male dominated to a female dominated occupation and the log odds of moving from a female dominated to a male dominated occupations.

Overall, these comparisons give me general confidence that the coefficients in the original models are not unduly biased by the IIA assumption or unobserved heterogeneity. However, there are some differences between the random effects and original models. In particular, given the differences in the education coefficients, it is important to explore whether
the interaction terms between education and time vary using the two different approaches. Thus I think it is appropriate to work toward improving the random effects models using alternative maximization methods to hopefully get the discrete factor method to work. If this is possible, it would also make using the random effects models more feasible as the discrete factor estimation is much faster than estimation using normally distributed random effects, As I have noted, the random effects models are not a perfect solution due to the fact that the portion of the sample who have multiple spells is only 50-75% for the samples originating in female dominated and integrated occupations and 25-50% for the sample originating in male dominated occupations. However, I think it would be useful to pursue the discrete factor method further and compare the coefficients from both Models 3 and 4 to the respective coefficients using discrete factor estimation.
Table 4.1: Matched Pairs of Two Year Intervals

<table>
<thead>
<tr>
<th>NLS Mature Women</th>
<th>NLS Young Women</th>
<th>NLSY79</th>
<th>NLSY97</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>2008-2010</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>2010-2012</td>
<td></td>
</tr>
</tbody>
</table>

Only years for which at least some women in the survey are aged 23-65 are included in the table.
Figure 4.1: Mean and Median Percentage Female in Women's Occupations
Figure 4.2: Percent of Women in Occupation Categories over Time
Figure 4.3: Percent of Labor Force in Occupation Categories over Time

- Male Dominated
- Integrated
- Female Dominated
Table 4.2: Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean/Percentage</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>White</td>
<td>61%</td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>28%</td>
<td></td>
</tr>
<tr>
<td>Latino</td>
<td>10%</td>
<td></td>
</tr>
<tr>
<td>Multiracial/Other Race</td>
<td>1%</td>
<td></td>
</tr>
<tr>
<td>No High School Diploma</td>
<td>16%</td>
<td></td>
</tr>
<tr>
<td>High School Diploma</td>
<td>39%</td>
<td></td>
</tr>
<tr>
<td>Some College</td>
<td>23%</td>
<td></td>
</tr>
<tr>
<td>Bachelor’s Degree</td>
<td>22%</td>
<td></td>
</tr>
<tr>
<td>Married</td>
<td>58%</td>
<td></td>
</tr>
<tr>
<td>Widowed/Divorced/Separated</td>
<td>21%</td>
<td></td>
</tr>
<tr>
<td>Never Been Married</td>
<td>22%</td>
<td></td>
</tr>
<tr>
<td>Child under 5 years</td>
<td>17%</td>
<td></td>
</tr>
<tr>
<td>Child 5-17 years</td>
<td>32%</td>
<td></td>
</tr>
<tr>
<td>No child in home</td>
<td>52%</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>36.8</td>
<td>9.5</td>
</tr>
<tr>
<td>Years in Occupation</td>
<td>4.9</td>
<td>4.6</td>
</tr>
<tr>
<td>Weeks of Work Experience</td>
<td>546.1</td>
<td>372.7</td>
</tr>
<tr>
<td>Part Time Worker</td>
<td>25%</td>
<td></td>
</tr>
</tbody>
</table>

Sample Size: 96,673 person-years
**Table 4.3: Change in Fraction Female**

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-1 to -.3</td>
<td>-.3 to -1</td>
<td>-1 to .3</td>
</tr>
<tr>
<td></td>
<td>Coeff. SE</td>
<td>Coeff. SE</td>
<td>Coeff. SE</td>
</tr>
<tr>
<td>Age</td>
<td>-0.055*** (0.002)</td>
<td>-0.056*** (0.001)</td>
<td>-0.052*** (0.001)</td>
</tr>
<tr>
<td>Year</td>
<td>-0.016*** (0.001)</td>
<td>-0.007*** (0.001)</td>
<td>-0.010*** (0.001)</td>
</tr>
<tr>
<td>Constant</td>
<td>31.230*** (2.043)</td>
<td>14.245*** (2.010)</td>
<td>19.880*** (1.904)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-1 to -.3</td>
<td>-.3 to -1</td>
<td>-1 to .3</td>
</tr>
<tr>
<td></td>
<td>Coeff. SE</td>
<td>Coeff. SE</td>
<td>Coeff. SE</td>
</tr>
<tr>
<td>Age</td>
<td>-0.052*** (0.002)</td>
<td>-0.055*** (0.001)</td>
<td>-0.051*** (0.001)</td>
</tr>
<tr>
<td>Year</td>
<td>-0.011*** (0.001)</td>
<td>-0.006*** (0.001)</td>
<td>-0.009*** (0.001)</td>
</tr>
<tr>
<td>Frac Fem in Occ</td>
<td>3.541*** (0.071)</td>
<td>0.921*** (0.060)</td>
<td>0.246*** (0.058)</td>
</tr>
<tr>
<td>Constant</td>
<td>18.535*** (2.196)</td>
<td>11.034*** (2.029)</td>
<td>19.078*** (1.889)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-1 to -.3</td>
<td>-.3 to -1</td>
<td>-1 to .3</td>
</tr>
<tr>
<td></td>
<td>Coeff. SE</td>
<td>Coeff. SE</td>
<td>Coeff. SE</td>
</tr>
<tr>
<td>Age</td>
<td>-0.031*** (0.002)</td>
<td>-0.033*** (0.002)</td>
<td>-0.025*** (0.002)</td>
</tr>
<tr>
<td>Year</td>
<td>-0.002</td>
<td>-0.001</td>
<td>-0.004** (0.001)</td>
</tr>
<tr>
<td>Frac Fem in Occ</td>
<td>3.977*** (0.071)</td>
<td>1.259*** (0.060)</td>
<td>0.506*** (0.056)</td>
</tr>
<tr>
<td>Years in Occ</td>
<td>-0.149*** (0.005)</td>
<td>-0.147*** (0.005)</td>
<td>-0.162*** (0.004)</td>
</tr>
<tr>
<td>Black</td>
<td>-0.112** (0.034)</td>
<td>-0.067* (0.031)</td>
<td>0.024</td>
</tr>
<tr>
<td>Latino/Other</td>
<td>-0.147* (0.048)</td>
<td>-0.031 (0.042)</td>
<td>0.034</td>
</tr>
<tr>
<td>Bachelor’s Deg</td>
<td>-0.276*** (0.041)</td>
<td>0.049 (0.034)</td>
<td>-0.112*** (0.033)</td>
</tr>
<tr>
<td>Some College</td>
<td>-0.107* (0.037)</td>
<td>-0.003 (0.033)</td>
<td>0.049</td>
</tr>
<tr>
<td>No High Sch Dip</td>
<td>0.303*** (0.041)</td>
<td>0.085* (0.040)</td>
<td>-0.052</td>
</tr>
<tr>
<td>Wid/Div/Sep</td>
<td>0.209*** (0.036)</td>
<td>0.133*** (0.033)</td>
<td>0.154*** (0.030)</td>
</tr>
<tr>
<td>Never Married</td>
<td>0.136*** (0.039)</td>
<td>0.128*** (0.035)</td>
<td>0.098** (0.033)</td>
</tr>
<tr>
<td>Child under 5</td>
<td>0.044</td>
<td>0.031 (0.036)</td>
<td>0.120*** (0.033)</td>
</tr>
<tr>
<td>Child 5-17</td>
<td>0.067* (0.032)</td>
<td>0.097*** (0.030)</td>
<td>0.134*** (0.027)</td>
</tr>
<tr>
<td>Work Exper</td>
<td>0.0002* (0.0001)</td>
<td>0.0002*** (0.0001)</td>
<td>0.0001</td>
</tr>
<tr>
<td>Part-time Work</td>
<td>0.095** (0.030)</td>
<td>0.034 (0.029)</td>
<td>0.135*** (0.026)</td>
</tr>
<tr>
<td>Unemp Rate</td>
<td>0.085*** (0.007)</td>
<td>0.067*** (0.007)</td>
<td>0.084*** (0.006)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.859 (2.960)</td>
<td>1.476 (2.675)</td>
<td>6.225* (2.479)</td>
</tr>
<tr>
<td>Sample</td>
<td>96,673</td>
<td>96,673</td>
<td>96,673</td>
</tr>
</tbody>
</table>

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1
Figure 4.4 Probability of Occupational Transitions by Year and Model

- Change Fraction Female -1 to -.3
- Change Fraction Female -.3 to -.1
- Change Fraction Female -.1 to .1
- Change Fraction Female .1 to .3
- Change Fraction Female .3 to 1
- Same Occupation
Table 4.4: Occupational Transitions, Originated Male Dominated Occupation

<table>
<thead>
<tr>
<th>Outcome:</th>
<th>Male Dominated</th>
<th>Model 1</th>
<th>Female Dominated</th>
<th>Male Dominated</th>
<th>Model 2</th>
<th>Female Dominated</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>Coeff. (SE)</td>
<td>Coeff. (SE)</td>
<td>Coeff. (SE)</td>
<td>Coeff. (SE)</td>
<td>Coeff. (SE)</td>
<td>Coeff. (SE)</td>
</tr>
<tr>
<td>Year</td>
<td>-0.071*** (0.005)</td>
<td>-0.059*** (0.004)</td>
<td>-0.062*** (0.004)</td>
<td>-0.065*** (0.005)</td>
<td>-0.054*** (0.004)</td>
<td>-0.060*** (0.004)</td>
</tr>
<tr>
<td>% Male Dom Occ</td>
<td>-0.019*** (0.003)</td>
<td>-0.010*** (0.002)</td>
<td>-0.027*** (0.003)</td>
<td>-0.055*** (0.007)</td>
<td>-0.045*** (0.005)</td>
<td>-0.040*** (0.005)</td>
</tr>
<tr>
<td>% Fem Dom Occ</td>
<td>-0.062*** (0.014)</td>
<td>-0.051*** (0.011)</td>
<td>-0.020+ (0.012)</td>
<td>-0.020+ (0.012)</td>
<td>-0.020+ (0.012)</td>
<td>-0.020+ (0.012)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Outcome:</th>
<th>Male Dominated</th>
<th>Model 3</th>
<th>Female Dominated</th>
<th>Male Dominated</th>
<th>Model 4</th>
<th>Female Dominated</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>Coeff. (SE)</td>
<td>Coeff. (SE)</td>
<td>Coeff. (SE)</td>
<td>Coeff. (SE)</td>
<td>Coeff. (SE)</td>
<td>Coeff. (SE)</td>
</tr>
<tr>
<td>Year</td>
<td>-0.044*** (0.006)</td>
<td>-0.033*** (0.005)</td>
<td>-0.023*** (0.005)</td>
<td>-0.045*** (0.006)</td>
<td>-0.033*** (0.005)</td>
<td>-0.024*** (0.005)</td>
</tr>
<tr>
<td>% Male Dom Occ</td>
<td>-0.068*** (0.014)</td>
<td>-0.054*** (0.011)</td>
<td>-0.023+ (0.012)</td>
<td>-0.066*** (0.014)</td>
<td>-0.056*** (0.011)</td>
<td>-0.021+ (0.012)</td>
</tr>
<tr>
<td>% Fem Dom Occ</td>
<td>-0.209* (0.087)</td>
<td>-0.251*** (0.067)</td>
<td>-0.122+ (0.063)</td>
<td>-0.214* (0.088)</td>
<td>-0.265*** (0.068)</td>
<td>-0.134* (0.064)</td>
</tr>
<tr>
<td>Years in Occ</td>
<td>-0.128*** (0.016)</td>
<td>-0.198*** (0.013)</td>
<td>-0.217*** (0.015)</td>
<td>-0.129*** (0.016)</td>
<td>-0.198*** (0.013)</td>
<td>-0.218*** (0.015)</td>
</tr>
<tr>
<td>Black</td>
<td>-0.212* (0.103)</td>
<td>-0.005 (0.072)</td>
<td>0.009 (0.077)</td>
<td>-0.181+ (0.104)</td>
<td>-0.008 (0.072)</td>
<td>0.039 (0.077)</td>
</tr>
<tr>
<td>Latino/Other</td>
<td>-0.182 (0.147)</td>
<td>0.082 (0.109)</td>
<td>0.123 (0.114)</td>
<td>-0.184 (0.147)</td>
<td>0.096 (0.109)</td>
<td>0.130 (0.115)</td>
</tr>
<tr>
<td>Bachelor’s Deg</td>
<td>-0.218+ (0.129)</td>
<td>-0.016 (0.083)</td>
<td>-0.436*** (0.093)</td>
<td>-0.718* (0.280)</td>
<td>-0.440* (0.199)</td>
<td>-1.117*** (0.200)</td>
</tr>
<tr>
<td>Some College</td>
<td>0.012 (0.114)</td>
<td>0.008 (0.080)</td>
<td>0.194* (0.081)</td>
<td>-0.037 (0.262)</td>
<td>-0.240 (0.196)</td>
<td>0.206 (0.179)</td>
</tr>
<tr>
<td>No High Sch Dip</td>
<td>0.185 (0.116)</td>
<td>0.235** (0.082)</td>
<td>-0.134 (0.085)</td>
<td>-0.382+ (0.213)</td>
<td>0.179 (0.159)</td>
<td>-0.556*** (0.156)</td>
</tr>
<tr>
<td>Wid/Div/Sep</td>
<td>0.143 (0.102)</td>
<td>0.055 (0.073)</td>
<td>0.006 (0.080)</td>
<td>0.346 (0.102)</td>
<td>0.064 (0.073)</td>
<td>0.015 (0.080)</td>
</tr>
<tr>
<td>Never Married</td>
<td>0.244* (0.123)</td>
<td>-0.052 (0.085)</td>
<td>0.006 (0.091)</td>
<td>0.246* (0.124)</td>
<td>-0.041 (0.085)</td>
<td>0.012 (0.091)</td>
</tr>
<tr>
<td>Child under 5</td>
<td>-0.092 (0.121)</td>
<td>-0.128 (0.091)</td>
<td>0.092 (0.093)</td>
<td>-0.083 (0.121)</td>
<td>-0.132 (0.091)</td>
<td>0.101 (0.093)</td>
</tr>
<tr>
<td>Child 5-17</td>
<td>0.046 (0.101)</td>
<td>0.167* (0.067)</td>
<td>0.042 (0.074)</td>
<td>0.042 (0.100)</td>
<td>0.160* (0.068)</td>
<td>0.036 (0.074)</td>
</tr>
<tr>
<td>Work Exper</td>
<td>-0.0001 (0.0002)</td>
<td>0.0001 (0.0001)</td>
<td>-0.0006*** (0.0002)</td>
<td>-0.00004 (0.0002)</td>
<td>0.00001 (0.0001)</td>
<td>-0.0006*** (0.0002)</td>
</tr>
<tr>
<td>Part-time Work</td>
<td>-0.175+ (0.101)</td>
<td>-0.171* (0.075)</td>
<td>0.221** (0.074)</td>
<td>-0.165 (0.101)</td>
<td>-0.173* (0.075)</td>
<td>0.230** (0.074)</td>
</tr>
<tr>
<td>Unemp Rate</td>
<td>0.014 (0.025)</td>
<td>0.058** (0.018)</td>
<td>0.004 (0.019)</td>
<td>0.011 (0.025)</td>
<td>0.057** (0.018)</td>
<td>-0.0004 (0.019)</td>
</tr>
<tr>
<td>BA- Year Int.</td>
<td>0.020* (0.010)</td>
<td>0.016* (0.007)</td>
<td>0.028*** (0.007)</td>
<td>0.020* (0.010)</td>
<td>0.016* (0.007)</td>
<td>0.028*** (0.007)</td>
</tr>
<tr>
<td>NHS-Year Int.</td>
<td>0.028** (0.009)</td>
<td>0.002 (0.006)</td>
<td>0.027** (0.007)</td>
<td>0.028** (0.009)</td>
<td>0.002 (0.006)</td>
<td>0.027** (0.007)</td>
</tr>
<tr>
<td>SC-Year Int.</td>
<td>0.003 (0.010)</td>
<td>0.010 (0.007)</td>
<td>0.000 (0.007)</td>
<td>0.003 (0.010)</td>
<td>0.010 (0.007)</td>
<td>0.000 (0.007)</td>
</tr>
<tr>
<td>Constant</td>
<td>99.351*** (15.293)</td>
<td>73.280*** (11.347)</td>
<td>43.047*** (11.839)</td>
<td>120.699*** (17.868)</td>
<td>87.955*** (13.220)</td>
<td>63.016*** (13.687)</td>
</tr>
</tbody>
</table>

Sample 9,696  9,696  9,696  9,696  9,696  9,696

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1
Table 4.5: Occupational Transitions, Originated Integrated Occupation

<table>
<thead>
<tr>
<th>Outcome:</th>
<th>Male Dominated</th>
<th>Model 1</th>
<th>Female Dominated</th>
<th>Male Dominated</th>
<th>Model 2</th>
<th>Female Dominated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff</td>
<td>SE</td>
<td>Coeff</td>
<td>SE</td>
<td>Coeff</td>
<td>SE</td>
</tr>
<tr>
<td>Age</td>
<td>-0.054*** (0.003)</td>
<td>-0.059*** (0.002)</td>
<td>-0.065*** (0.002)</td>
<td>-0.053*** (0.003)</td>
<td>-0.055*** (0.002)</td>
<td>-0.062*** (0.002)</td>
</tr>
<tr>
<td>Year</td>
<td>-0.016*** (0.002)</td>
<td>-0.008*** (0.001)</td>
<td>-0.012*** (0.001)</td>
<td>-0.044*** (0.003)</td>
<td>-0.056*** (0.002)</td>
<td>-0.048*** (0.002)</td>
</tr>
<tr>
<td>% Male Dom Occ</td>
<td>-0.044*** (0.008)</td>
<td>-0.097*** (0.005)</td>
<td>-0.070*** (0.006)</td>
<td>-0.043*** (0.008)</td>
<td>-0.098*** (0.005)</td>
<td>-0.066*** (0.006)</td>
</tr>
<tr>
<td>% Fem Dom Occ</td>
<td>-0.244*** (0.053)</td>
<td>-0.260*** (0.037)</td>
<td>-0.234*** (0.036)</td>
<td>-0.241*** (0.053)</td>
<td>-0.263*** (0.037)</td>
<td>-0.221*** (0.036)</td>
</tr>
<tr>
<td>Years in Occ</td>
<td>-0.124*** (0.009)</td>
<td>-0.152*** (0.006)</td>
<td>-0.177*** (0.007)</td>
<td>-0.124*** (0.009)</td>
<td>-0.152*** (0.006)</td>
<td>-0.179*** (0.007)</td>
</tr>
<tr>
<td>Black</td>
<td>-0.137* (0.060)</td>
<td>-0.097* (0.038)</td>
<td>0.065* (0.039)</td>
<td>-0.135* (0.059)</td>
<td>-0.097* (0.038)</td>
<td>0.071* (0.039)</td>
</tr>
<tr>
<td>Latino/Other</td>
<td>-0.056 (0.087)</td>
<td>0.010 (0.052)</td>
<td>0.131* (0.055)</td>
<td>-0.061 (0.087)</td>
<td>0.008 (0.052)</td>
<td>0.107* (0.056)</td>
</tr>
<tr>
<td>Bachelor’s Deg</td>
<td>-0.372*** (0.068)</td>
<td>-0.004 (0.041)</td>
<td>-0.324*** (0.045)</td>
<td>-0.870*** (0.162)</td>
<td>-0.156 (0.100)</td>
<td>-0.240* (0.101)</td>
</tr>
<tr>
<td>Some College</td>
<td>-0.187** (0.070)</td>
<td>0.047 (0.044)</td>
<td>0.140** (0.043)</td>
<td>-0.066 (0.181)</td>
<td>-0.097 (0.119)</td>
<td>0.113 (0.110)</td>
</tr>
<tr>
<td>No High Sch Dip</td>
<td>0.143* (0.069)</td>
<td>0.104* (0.046)</td>
<td>-0.245*** (0.049)</td>
<td>-0.147 (0.123)</td>
<td>0.020 (0.093)</td>
<td>-0.644*** (0.089)</td>
</tr>
<tr>
<td>Wid/Div/Sep</td>
<td>0.178** (0.061)</td>
<td>0.130** (0.040)</td>
<td>0.116** (0.041)</td>
<td>0.179** (0.061)</td>
<td>0.131** (0.040)</td>
<td>0.112** (0.041)</td>
</tr>
<tr>
<td>Never Married</td>
<td>0.148* (0.069)</td>
<td>0.150*** (0.043)</td>
<td>0.082* (0.045)</td>
<td>0.152* (0.069)</td>
<td>0.152*** (0.043)</td>
<td>0.073 (0.045)</td>
</tr>
<tr>
<td>Child under 5</td>
<td>0.077 (0.071)</td>
<td>0.004 (0.045)</td>
<td>0.155*** (0.045)</td>
<td>0.076 (0.071)</td>
<td>0.004 (0.045)</td>
<td>0.149*** (0.045)</td>
</tr>
<tr>
<td>Child 5-17</td>
<td>0.194*** (0.056)</td>
<td>0.020 (0.037)</td>
<td>0.135*** (0.038)</td>
<td>0.188*** (0.056)</td>
<td>0.019 (0.037)</td>
<td>0.132*** (0.038)</td>
</tr>
<tr>
<td>Work Exp</td>
<td>0.0002 (0.0001)</td>
<td>-0.0003*** (0.0001)</td>
<td>-0.0006*** (0.0001)</td>
<td>0.0002 (0.0001)</td>
<td>-0.0003*** (0.0001)</td>
<td>-0.0005*** (0.0001)</td>
</tr>
<tr>
<td>Part-time Work</td>
<td>-0.077 (0.060)</td>
<td>0.015 (0.037)</td>
<td>0.334*** (0.036)</td>
<td>-0.073 (0.060)</td>
<td>0.016 (0.037)</td>
<td>0.332*** (0.036)</td>
</tr>
<tr>
<td>Unemp Rate</td>
<td>0.007 (0.015)</td>
<td>0.074*** (0.009)</td>
<td>0.050*** (0.009)</td>
<td>0.004 (0.015)</td>
<td>0.074*** (0.009)</td>
<td>0.047*** (0.009)</td>
</tr>
<tr>
<td>BA- Year Int.</td>
<td>0.020*** (0.006)</td>
<td>0.006+ (0.004)</td>
<td>-0.003 (0.004)</td>
<td>0.014* (0.005)</td>
<td>0.004 (0.004)</td>
<td>0.020*** (0.004)</td>
</tr>
<tr>
<td>NHS-Year Int.</td>
<td>0.014** (0.005)</td>
<td>0.004 (0.004)</td>
<td>0.020*** (0.004)</td>
<td>-0.004 (0.006)</td>
<td>0.006 (0.004)</td>
<td>0.001 (0.004)</td>
</tr>
<tr>
<td>SC-Year Int.</td>
<td>0.014** (0.005)</td>
<td>0.004 (0.004)</td>
<td>0.020*** (0.004)</td>
<td>-0.004 (0.006)</td>
<td>0.006 (0.004)</td>
<td>0.001 (0.004)</td>
</tr>
<tr>
<td>Constant</td>
<td>85.043*** (8.204)</td>
<td>102.581*** (5.365)</td>
<td>83.407*** (5.408)</td>
<td>98.594*** (10.103)</td>
<td>110.172*** (6.696)</td>
<td>86.649*** (6.531)</td>
</tr>
</tbody>
</table>

Sample 36,272  36,272  36,272  36,272  36,272  36,272  36,272

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1
Table 4.6: Occupational Transitions, Originated Female Dominated Occupation

<table>
<thead>
<tr>
<th>Outcome:</th>
<th>Male Dominated</th>
<th>Model 1 Integrated</th>
<th>Female Dominated</th>
<th>Male Dominated</th>
<th>Model 2 Integrated</th>
<th>Female Dominated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff.</td>
<td>SE</td>
<td>Coeff.</td>
<td>SE</td>
<td>Coeff.</td>
<td>SE</td>
</tr>
<tr>
<td>Age</td>
<td>-0.037***</td>
<td>(0.003)</td>
<td>-0.053***</td>
<td>(0.002)</td>
<td>-0.047***</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Year</td>
<td>-0.026***</td>
<td>(0.002)</td>
<td>0.0002</td>
<td>(0.001)</td>
<td>-0.015***</td>
<td>(0.001)</td>
</tr>
<tr>
<td>% Male Dom Occ</td>
<td>0.005</td>
<td>(0.008)</td>
<td>-0.063***</td>
<td>(0.004)</td>
<td>-0.049***</td>
<td>(0.004)</td>
</tr>
<tr>
<td>% Fem Dom Occ</td>
<td>-0.055</td>
<td>(0.042)</td>
<td>-0.386***</td>
<td>(0.030)</td>
<td>-0.231***</td>
<td>(0.024)</td>
</tr>
<tr>
<td>Constant</td>
<td>50.974***</td>
<td>(4.208)</td>
<td>0.169</td>
<td>(2.273)</td>
<td>30.189***</td>
<td>(2.115)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Outcome:</th>
<th>Male Dominated</th>
<th>Model 3 Integrated</th>
<th>Female Dominated</th>
<th>Male Dominated</th>
<th>Model 4 Integrated</th>
<th>Female Dominated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff.</td>
<td>SE</td>
<td>Coeff.</td>
<td>SE</td>
<td>Coeff.</td>
<td>SE</td>
</tr>
<tr>
<td>Age</td>
<td>-0.017***</td>
<td>(0.004)</td>
<td>-0.027***</td>
<td>(0.002)</td>
<td>-0.019***</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Year</td>
<td>-0.019***</td>
<td>(0.004)</td>
<td>-0.036***</td>
<td>(0.002)</td>
<td>-0.038***</td>
<td>(0.002)</td>
</tr>
<tr>
<td>% Male Dom Occ</td>
<td>-0.006</td>
<td>(0.009)</td>
<td>-0.074***</td>
<td>(0.005)</td>
<td>-0.053***</td>
<td>(0.004)</td>
</tr>
<tr>
<td>% Fem Dom Occ</td>
<td>-0.080+</td>
<td>(0.046)</td>
<td>-0.312***</td>
<td>(0.032)</td>
<td>-0.204***</td>
<td>(0.026)</td>
</tr>
<tr>
<td>Years in Occ</td>
<td>-0.154***</td>
<td>(0.009)</td>
<td>-0.144***</td>
<td>(0.005)</td>
<td>-0.163***</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Black</td>
<td>-0.198**</td>
<td>(0.062)</td>
<td>0.006</td>
<td>(0.035)</td>
<td>0.010</td>
<td>(0.032)</td>
</tr>
<tr>
<td>Latino/Other</td>
<td>-0.185+</td>
<td>(0.097)</td>
<td>-0.122*</td>
<td>(0.050)</td>
<td>0.041</td>
<td>(0.042)</td>
</tr>
<tr>
<td>Bachelor’s Deg</td>
<td>-0.268***</td>
<td>(0.078)</td>
<td>0.020</td>
<td>(0.041)</td>
<td>-0.342***</td>
<td>(0.039)</td>
</tr>
<tr>
<td>Some College</td>
<td>-0.024</td>
<td>(0.066)</td>
<td>-0.049</td>
<td>(0.038)</td>
<td>0.021</td>
<td>(0.031)</td>
</tr>
<tr>
<td>No High Sch Dip</td>
<td>0.265***</td>
<td>(0.074)</td>
<td>0.180***</td>
<td>(0.045)</td>
<td>-0.217***</td>
<td>(0.042)</td>
</tr>
<tr>
<td>Wid/Div/ Sep</td>
<td>0.215**</td>
<td>(0.066)</td>
<td>0.146***</td>
<td>(0.038)</td>
<td>0.108**</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Never Married</td>
<td>0.135+</td>
<td>(0.074)</td>
<td>0.101*</td>
<td>(0.040)</td>
<td>0.050</td>
<td>(0.036)</td>
</tr>
<tr>
<td>Child under 5</td>
<td>0.003</td>
<td>(0.073)</td>
<td>-0.031</td>
<td>(0.040)</td>
<td>0.060+</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Child 5-17</td>
<td>0.130*</td>
<td>(0.059)</td>
<td>-0.019</td>
<td>(0.034)</td>
<td>0.084**</td>
<td>(0.029)</td>
</tr>
<tr>
<td>Work Exper</td>
<td>0.0003</td>
<td>(0.0001)</td>
<td>0.0001</td>
<td>(0.0001)</td>
<td>0.0004</td>
<td>(0.0001)</td>
</tr>
<tr>
<td>Part-time Work</td>
<td>0.109*</td>
<td>(0.055)</td>
<td>0.133***</td>
<td>(0.032)</td>
<td>0.148***</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Unemp Rate</td>
<td>0.002</td>
<td>(0.014)</td>
<td>0.064***</td>
<td>(0.008)</td>
<td>0.046***</td>
<td>(0.007)</td>
</tr>
<tr>
<td>BA- Year Int.</td>
<td>-0.008</td>
<td>(0.005)</td>
<td>-0.011***</td>
<td>(0.003)</td>
<td>0.023***</td>
<td>(0.003)</td>
</tr>
<tr>
<td>NHS-Year Int.</td>
<td>-0.006</td>
<td>(0.005)</td>
<td>-0.007*</td>
<td>(0.004)</td>
<td>0.013***</td>
<td>(0.003)</td>
</tr>
<tr>
<td>SC-Year Int.</td>
<td>-0.003</td>
<td>(0.005)</td>
<td>-0.002*</td>
<td>(0.003)</td>
<td>0.004</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Constant</td>
<td>39.266***</td>
<td>(8.866)</td>
<td>82.890***</td>
<td>(5.013)</td>
<td>84.445***</td>
<td>(4.517)</td>
</tr>
</tbody>
</table>

Sample: 50,705

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1
Figure 4.5: Probability of Occupational Transitions by Year and Occupation Gender Representation Category of Origin, Net of Age
Figure 4.6: Probability of Occupational Transitions by Year and Occupation Gender Representation Category of Origin, Net of National Occupational Distribution and Age.
Figure 4.7: Probability of Occupational Transitions by Year and Model, Originated Male Dominated Occupation

- Change to Male Dominated
- Change to Integrated
- Change to Female Dominated
- Same Occupation
Figure 4.8: Probability of Occupational Transitions by Year and Model, Originated Integrated Occupation
Figure 4.9: Probability of Occupational Transitions by Year and Model, Originated Female Dominated Occupation
Figure 4.10: Probabilities of Occupational Transitions by Year and Education Level (Model 4): Originated Male Dominated Occupation

- Same Occupation
- Change to Female Dominated
- Change to Integrated
- Change to Male Dominated
Figure 4.11: Probabilities of Occupational Transitions by Year and Education Level (Model 4): Originated Integrated Occupation
Figure 4.12: Probabilities of Occupational Transitions by Year and Education Level (Model 4): Originated Female Dominated Occupation

- Change to Male Dominated
- Change to Integrated
- Change to Female Dominated
- Same Occupation

Figure 4.13: Impact of Unemployment Rate on Probability of Occupation Transitions (Model 4 Coefficients)
Table 4.7: Occupational Transitions, Originated Male Dominated Occupation, RE

<table>
<thead>
<tr>
<th>Outcome:</th>
<th>Male Dominated</th>
<th></th>
<th>Integrated</th>
<th></th>
<th>Female Dominated</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff.</td>
<td>SE</td>
<td>Coeff</td>
<td>SE</td>
<td>Coeff.</td>
<td>SE</td>
</tr>
<tr>
<td>Age</td>
<td>-0.047***</td>
<td>(0.007)</td>
<td>-0.040***</td>
<td>(0.006)</td>
<td>-0.029***</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Year</td>
<td>-0.045***</td>
<td>(0.007)</td>
<td>-0.035***</td>
<td>(0.006)</td>
<td>-0.021***</td>
<td>(0.006)</td>
</tr>
<tr>
<td>% Male Dom Occ</td>
<td>-0.063***</td>
<td>(0.015)</td>
<td>-0.063***</td>
<td>(0.012)</td>
<td>-0.027*</td>
<td>(0.013)</td>
</tr>
<tr>
<td>% Fem Dom Occ</td>
<td>-0.228*</td>
<td>(0.093)</td>
<td>-0.266***</td>
<td>(0.074)</td>
<td>-0.134+</td>
<td>(0.072)</td>
</tr>
<tr>
<td>Years in Occ</td>
<td>-0.120***</td>
<td>(0.017)</td>
<td>-0.175***</td>
<td>(0.016)</td>
<td>-0.190***</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Black</td>
<td>-0.225*</td>
<td>(0.107)</td>
<td>0.026</td>
<td>(0.081)</td>
<td>0.048</td>
<td>(0.089)</td>
</tr>
<tr>
<td>Latino/Other</td>
<td>-0.155</td>
<td>(0.155)</td>
<td>0.102</td>
<td>(0.122)</td>
<td>0.141</td>
<td>(0.130)</td>
</tr>
<tr>
<td>Bachelor’s Deg</td>
<td>-0.227+</td>
<td>(0.128)</td>
<td>-0.022</td>
<td>(0.093)</td>
<td>-0.500***</td>
<td>(0.108)</td>
</tr>
<tr>
<td>Some College</td>
<td>0.036</td>
<td>(0.116)</td>
<td>0.009</td>
<td>(0.090)</td>
<td>0.200*</td>
<td>(0.094)</td>
</tr>
<tr>
<td>No High Sch Dip</td>
<td>0.190</td>
<td>(0.121)</td>
<td>0.264**</td>
<td>(0.093)</td>
<td>-0.173+</td>
<td>(0.100)</td>
</tr>
<tr>
<td>Wid/Div/Sep</td>
<td>0.153</td>
<td>(0.107)</td>
<td>0.080</td>
<td>(0.081)</td>
<td>0.020</td>
<td>(0.090)</td>
</tr>
<tr>
<td>Never Married</td>
<td>0.235+</td>
<td>(0.124)</td>
<td>-0.077</td>
<td>(0.095)</td>
<td>0.008</td>
<td>(0.105)</td>
</tr>
<tr>
<td>Child under 5</td>
<td>-0.075</td>
<td>(0.128)</td>
<td>-0.162</td>
<td>(0.101)</td>
<td>0.100</td>
<td>(0.106)</td>
</tr>
<tr>
<td>Child 5-17</td>
<td>0.054</td>
<td>(0.105)</td>
<td>0.179*</td>
<td>(0.075)</td>
<td>0.061</td>
<td>(0.084)</td>
</tr>
<tr>
<td>Work Exper</td>
<td>-0.0002</td>
<td>(0.0002)</td>
<td>0.0001</td>
<td>(0.0002)</td>
<td>-0.0007***</td>
<td>(0.0002)</td>
</tr>
<tr>
<td>Part-time Work</td>
<td>-0.174</td>
<td>(0.108)</td>
<td>-0.190*</td>
<td>(0.082)</td>
<td>0.242**</td>
<td>(0.084)</td>
</tr>
<tr>
<td>Unemp Rate</td>
<td>0.017</td>
<td>(0.026)</td>
<td>0.067***</td>
<td>(0.020)</td>
<td>0.002</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Constant</td>
<td>99.048***</td>
<td>(15.993)</td>
<td>81.046***</td>
<td>(12.663)</td>
<td>48.380***</td>
<td>(13.640)</td>
</tr>
</tbody>
</table>

Cor(u_{1i}, u_{2i}) = 0.01    Cor(u_{1i}, u_{3i}) = 0.07    Cor(u_{2i}, u_{3i}) = 0.35

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1
Table 4.8: Occupational Transitions, Originated Integrated Occupation, RE

<table>
<thead>
<tr>
<th>Outcome:</th>
<th>Male Dominated Coeff.</th>
<th>SE</th>
<th>Integrated Coeff.</th>
<th>SE</th>
<th>Female Dominated Coeff.</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>-0.043*** (0.004)</td>
<td></td>
<td>-0.027*** (0.003)</td>
<td></td>
<td>-0.029*** (0.003)</td>
<td></td>
</tr>
<tr>
<td>Year</td>
<td>-0.040*** (0.004)</td>
<td></td>
<td>-0.048*** (0.003)</td>
<td></td>
<td>-0.040*** (0.003)</td>
<td></td>
</tr>
<tr>
<td>% Male Dom Occ</td>
<td>-0.045*** (0.009)</td>
<td></td>
<td>-0.103*** (0.006)</td>
<td></td>
<td>-0.078*** (0.006)</td>
<td></td>
</tr>
<tr>
<td>% Fem Dom Occ</td>
<td>-0.246*** (0.057)</td>
<td></td>
<td>-0.269*** (0.039)</td>
<td></td>
<td>-0.241*** (0.040)</td>
<td></td>
</tr>
<tr>
<td>Years in Occ</td>
<td>-0.110*** (0.010)</td>
<td></td>
<td>-0.134*** (0.006)</td>
<td></td>
<td>-0.153*** (0.008)</td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>-0.157* (0.064)</td>
<td></td>
<td>-0.110** (0.040)</td>
<td></td>
<td>0.084+ (0.045)</td>
<td></td>
</tr>
<tr>
<td>Latino/Other</td>
<td>0.057 (0.093)</td>
<td></td>
<td>0.013 (0.055)</td>
<td></td>
<td>0.152* (0.064)</td>
<td></td>
</tr>
<tr>
<td>Bachelor’s Deg</td>
<td>-0.393*** (0.073)</td>
<td></td>
<td>-0.021 (0.044)</td>
<td></td>
<td>-0.377*** (0.052)</td>
<td></td>
</tr>
<tr>
<td>Some College</td>
<td>-0.204** (0.075)</td>
<td></td>
<td>0.047 (0.046)</td>
<td></td>
<td>0.150** (0.050)</td>
<td></td>
</tr>
<tr>
<td>No High Sch Dip</td>
<td>0.157* (0.074)</td>
<td></td>
<td>0.102* (0.048)</td>
<td></td>
<td>-0.297*** (0.056)</td>
<td></td>
</tr>
<tr>
<td>Wid/Div/Sep</td>
<td>0.166* (0.065)</td>
<td></td>
<td>0.128** (0.042)</td>
<td></td>
<td>0.122** (0.047)</td>
<td></td>
</tr>
<tr>
<td>Never Married</td>
<td>0.146* (0.073)</td>
<td></td>
<td>0.153*** (0.045)</td>
<td></td>
<td>0.078 (0.051)</td>
<td></td>
</tr>
<tr>
<td>Child under 5</td>
<td>0.078 (0.075)</td>
<td></td>
<td>0.007 (0.047)</td>
<td></td>
<td>0.172*** (0.050)</td>
<td></td>
</tr>
<tr>
<td>Child 5-17</td>
<td>0.205*** (0.059)</td>
<td></td>
<td>0.036 (0.039)</td>
<td></td>
<td>0.156*** (0.043)</td>
<td></td>
</tr>
<tr>
<td>Work Exper</td>
<td>0.0001 (0.0001)</td>
<td></td>
<td>-0.0004*** (0.0001)</td>
<td></td>
<td>-0.0006*** (0.0001)</td>
<td></td>
</tr>
<tr>
<td>Part-time Work</td>
<td>-0.051 (0.064)</td>
<td></td>
<td>0.035 (0.039)</td>
<td></td>
<td>0.346*** (0.041)</td>
<td></td>
</tr>
<tr>
<td>Unemp Rate</td>
<td>0.011 (0.016)</td>
<td></td>
<td>0.079*** (0.010)</td>
<td></td>
<td>0.052*** (0.010)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>87.441*** (9.730)</td>
<td></td>
<td>108.119*** (5.715)</td>
<td></td>
<td>89.370*** (6.144)</td>
<td></td>
</tr>
</tbody>
</table>

Sample 36,272

Cor(u1i, u2i) = 0.56  Cor(u1i, u3i) = -0.18  Cor(u2i, u3i) = 0.17

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1
Table 4.9: Occupational Transitions, Originated Female Dominated Occupation, RE

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Male Dominated</th>
<th>Integrated</th>
<th>Female Dominated</th>
<th>Coeff</th>
<th>SE</th>
<th>Coeff</th>
<th>SE</th>
<th>Coeff</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>-0.025***</td>
<td>-0.033***</td>
<td>-0.023***</td>
<td>(0.004)</td>
<td></td>
<td>(0.003)</td>
<td></td>
<td>(0.002)</td>
<td></td>
</tr>
<tr>
<td>Year</td>
<td>-0.024***</td>
<td>-0.040***</td>
<td>-0.041***</td>
<td>(0.005)</td>
<td></td>
<td>(0.003)</td>
<td></td>
<td>(0.002)</td>
<td></td>
</tr>
<tr>
<td>% Male Dom Occ</td>
<td>-0.014</td>
<td>-0.084***</td>
<td>-0.058***</td>
<td>(0.010)</td>
<td></td>
<td>(0.005)</td>
<td></td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td>% Fem Dom Occ</td>
<td>-0.101*</td>
<td>-0.328***</td>
<td>-0.217***</td>
<td>(0.051)</td>
<td></td>
<td>(0.035)</td>
<td></td>
<td>(0.027)</td>
<td></td>
</tr>
<tr>
<td>Years in Occ</td>
<td>-0.123***</td>
<td>-0.118***</td>
<td>-0.143***</td>
<td>(0.010)</td>
<td></td>
<td>(0.005)</td>
<td></td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>-0.210**</td>
<td>-0.007</td>
<td>0.004</td>
<td>(0.069)</td>
<td></td>
<td>(0.040)</td>
<td></td>
<td>(0.034)</td>
<td></td>
</tr>
<tr>
<td>Latino/Other</td>
<td>-0.219*</td>
<td>-0.145*</td>
<td>0.041</td>
<td>(0.105)</td>
<td></td>
<td>(0.057)</td>
<td></td>
<td>(0.046)</td>
<td></td>
</tr>
<tr>
<td>Bachelor’s Deg</td>
<td>-0.235**</td>
<td>0.059</td>
<td>-0.366***</td>
<td>(0.085)</td>
<td></td>
<td>(0.047)</td>
<td></td>
<td>(0.041)</td>
<td></td>
</tr>
<tr>
<td>Some College</td>
<td>-0.006</td>
<td>-0.034</td>
<td>0.027</td>
<td>(0.072)</td>
<td></td>
<td>(0.043)</td>
<td></td>
<td>(0.034)</td>
<td></td>
</tr>
<tr>
<td>No High Sch Dip</td>
<td>0.334***</td>
<td>0.232***</td>
<td>-0.214***</td>
<td>(0.082)</td>
<td></td>
<td>(0.052)</td>
<td></td>
<td>(0.044)</td>
<td></td>
</tr>
<tr>
<td>Wid/Div/Sep</td>
<td>0.203**</td>
<td>0.124**</td>
<td>0.112**</td>
<td>(0.072)</td>
<td></td>
<td>(0.042)</td>
<td></td>
<td>(0.035)</td>
<td></td>
</tr>
<tr>
<td>Never Married</td>
<td>0.141+</td>
<td>0.111*</td>
<td>0.048</td>
<td>(0.081)</td>
<td></td>
<td>(0.045)</td>
<td></td>
<td>(0.039)</td>
<td></td>
</tr>
<tr>
<td>Child under 5</td>
<td>0.009</td>
<td>-0.024</td>
<td>0.054</td>
<td>(0.079)</td>
<td></td>
<td>(0.044)</td>
<td></td>
<td>(0.038)</td>
<td></td>
</tr>
<tr>
<td>Child 5-17</td>
<td>0.154*</td>
<td>-0.010</td>
<td>0.083**</td>
<td>(0.063)</td>
<td></td>
<td>(0.038)</td>
<td></td>
<td>(0.031)</td>
<td></td>
</tr>
<tr>
<td>Work Exper</td>
<td>0.0001</td>
<td>0.0001</td>
<td>-0.0001</td>
<td>(0.0001)</td>
<td></td>
<td>(0.0001)</td>
<td></td>
<td>(0.0001)</td>
<td></td>
</tr>
<tr>
<td>Part-time Work</td>
<td>0.133*</td>
<td>0.148***</td>
<td>0.176***</td>
<td>(0.059)</td>
<td></td>
<td>(0.035)</td>
<td></td>
<td>(0.030)</td>
<td></td>
</tr>
<tr>
<td>Unemp Rate</td>
<td>0.004</td>
<td>0.069***</td>
<td>0.047***</td>
<td>(0.015)</td>
<td></td>
<td>(0.009)</td>
<td></td>
<td>(0.008)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>49.183***</td>
<td>92.667***</td>
<td>89.945***</td>
<td>(10.556)</td>
<td></td>
<td>(5.695)</td>
<td></td>
<td>(4.796)</td>
<td></td>
</tr>
<tr>
<td>Sample</td>
<td>50,705</td>
<td>50,705</td>
<td>50,705</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Cor(u_{1i}, u_{3i}) = 0.76 Cor(u_{1i}, u_{3i}) = 0.30 Cor(u_{2i}, u_{3i}) = 0.40

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1
Table 4.10: Ratio of Coefficients

<table>
<thead>
<tr>
<th>Coefficients:</th>
<th>Bachelor’s Degree to No High School Diploma</th>
<th>Unemployment Rate to United States Percent Female Dominated Occupation</th>
<th>Year to Age</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Male Dominated Coefficients</td>
<td>Integrated Coefficients</td>
<td>Female Dominated Coefficients</td>
</tr>
<tr>
<td>Originated Male Dominated</td>
<td>-1.18</td>
<td>-1.19</td>
<td>-0.07</td>
</tr>
<tr>
<td>Originated Integrated</td>
<td>-2.60</td>
<td>-2.50</td>
<td>-0.03</td>
</tr>
<tr>
<td>Originated Female Dominated</td>
<td>-1.01</td>
<td>-0.71</td>
<td>0.11</td>
</tr>
<tr>
<td>Originated Male Dominated</td>
<td>-0.07</td>
<td>-0.07</td>
<td>-0.23</td>
</tr>
<tr>
<td>Originated Integrated</td>
<td>-0.03</td>
<td>-0.04</td>
<td>-0.28</td>
</tr>
<tr>
<td>Originated Female Dominated</td>
<td>-0.03</td>
<td>-0.04</td>
<td>-0.21</td>
</tr>
<tr>
<td>Originated Male Dominated</td>
<td>1.02</td>
<td>0.96</td>
<td>0.97</td>
</tr>
<tr>
<td>Originated Integrated</td>
<td>1.00</td>
<td>0.93</td>
<td>2.00</td>
</tr>
<tr>
<td>Originated Female Dominated</td>
<td>1.12</td>
<td>0.96</td>
<td>1.33</td>
</tr>
</tbody>
</table>
Figure A.1 Labor Market Characteristics over Time

- Index of Dissimilarity
- Unemployment Rate
- % of Labor Force that is Female
- % White Collar Occupations
Figure A.2 Transition Percentages by Year: Originated Male Dominated Occupation

- Male Dominated
- Integrated
- Female Dominated
Figure A.3: Transition Percentages by Year: Originated Integrated Occupation

- Male Dominated
- Integrated
- Female Dominated
Figure A.4: Transition Percentages by Year: Originated Female Dominated Occupation

- Male Dominated
- Integrated
- Female Dominated
Figure A.5: Transition Percentages by Year

Change Fraction
Female -1 to -.3
Change Fraction
Female -.3 to -.1
Change Fraction
Female -.1 to .1
Change Fraction
Female .1 to .3
Change Fraction
Female .3 to 1
Figure A.6: Transition Percentages by Age: Early Cohort, Originated Male Dominated Occupation
Figure A.7: Transition Percentages by Age: Early Cohort, Originated Integrated Occupation

- Change to Male Dominated
- Change to Integrated
- Change to Female Dominated
Figure A.8: Transition Percentages by Age: Early Cohort, Originated Female Dominated Occupation

- Change to Male Dominated
- Change to Integrated
- Change to Female Dominated

Age

30 32 34 36 38 40 42 44 46 48 50 52 54 56 58 60 62
Figure A.9: Transition Percentages by Age: Original Cohort, Originated Male Dominated Occupation

- Change to Male Dominated
- Change to Integrated
- Change to Female Dominated

Age

0 5 10 15 20 25 30 35 40 45

23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53 55 57
Figure A.10: Transition Percentages by Age: Original Cohort, Originated Integrated Occupation

- Change to Male Dominated
- Change to Integrated
- Change to Female Dominated
Figure A.11: Transition Percentages by Age: Original Cohort, Originated Female Dominated Occupation

- Change to Male Dominated
- Change to Integrated
- Change to Female Dominated
Figure A.12: Transition Percentages by Age: Middle Cohort, Originated Male Dominated Occupation
Figure A.13: Transition Percentages by Age: Middle Cohort, Originated Integrated Occupation

- Male Dominated
- Integrated
- Female Dominated
Figure A.14: Transition Percentages by Age: Middle Cohort, Originated Female Dominated Occupation

- Male Dominated
- Integrated
- Female Dominated
Figure A.15: Transition Percentages by Age: Recent Cohort, Originated Male Dominated Occupation
Figure A.16: Transition Percentages by Age: Recent Cohort, Originated Integrated Occupation

- Male Dominated
- Integrated
- Female Dominated

Age
Figure A.17: Transition Percentages by Age: Recent Cohort. Originated Female Dominated Occupation

- Male Dominated
- Integrated
- Female Dominated
Figure A.18: Transition Percentages by Age: Early Cohort

Change Fraction Female -1 to -.3
Change Fraction Female -.3 to -.1
Change Fraction Female -.1 to .1
Change Fraction Female .1 to .3
Change Fraction Female .3 to 1
Figure A.19: Transition Percentages by Age: Original Cohort

Change Fraction Female -1 to -.3
Change Fraction Female -.3 to -.1
Change Fraction Female -.1 to .1
Change Fraction Female .1 to .3
Change Fraction Female .3 to 1
Figure A.20: Transition Percentage by Age: Middle Cohort

- Change Fraction Female -1 to -.3
- Change Fraction Female -.3 to -.1
- Change Fraction Female -.1 to .1
- Change Fraction Female .1 to .3
- Change Fraction Female .3 to 1

Age
Figure A.21: Transition Percentages by Age: Recent Cohort

Change Fraction Female
-1 to -.3
Change Fraction Female
-.3 to -.1
Change Fraction Female
-.1 to .1
Change Fraction Female
.1 to .3
Change Fraction Female
.3 to 1
Figure A.22: Transition Percentages by Years in Occupation, Originated Male Dominated Occupation

Change to Male Dominated
Change to Integrated
Change to Female Dominated
Figure A.23: Transition Percentages by Years in Occupation, Originated Integrated Occupation

- Change to Male Dominated
- Change to Integrated
- Change to Female Dominated

Years in Occupation
Figure A.24: Transition Percentages by Years in Occupation, Originated Female Dominated Occupation

- Change to Male Dominated
- Change to Integrated
- Change to Female Dominated

Years in Occupation:

1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33
Figure A.25: Transition Percentages by Years in Occupation

- Change Fraction Female -1 to -.3
- Change Fraction Female -.3 to -.1
- Change Fraction Female -.1 to .1
- Change Fraction Female .1 to .3
- Change Fraction Female .3 to 1

Years in Occupation
REFERENCES


Shin, Taek-Jin (2005). *Occupational Sex Segregation and Chances for Upward Mobility: Consequences of Job Shifts Within and Across Boundaries*. Paper Presented at the meeting of the Research Committee 28 on Social Stratification and Mobility at the University of California, Los Angeles.


