ESSAYS IN EARLY CHILDHOOD DEVELOPMENT AND PUBLIC POLICY

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Abstract

JADE VANESSA MARCUS JENKINS: Essays in early childhood development and public policy
(Under the direction of Gary T. Henry)

A large literature demonstrates the long-term individual and societal benefits of investing resources in children during early childhood because of the powerful influence of the environment during early life on child neurological development. Therefore, early childhood presents an unrivaled opportunity for policy intervention, and is a critical component of child and family policy.

This dissertation uses three different types of policy research to examine child well-being between birth and kindergarten. Chapter 1 is a *program evaluation* of a school-based outreach intervention to identify and enroll uninsured low-income children in publicly funded health insurance programs in North Carolina. Chapter 2 is a *state policy evaluation* examining how variations in state governance of early child care and education policy affects children's well-being. Chapter 3 is an example of *testing and applying theory* from economics to examine how parent characteristics and behaviors contribute to child cognitive development throughout early childhood. Each paper is interdisciplinary, implementing different methods for causal inference to address the unique challenges of each approach using statewide and nationally representative child data with several indicators of well-being.

In chapter one, there were no significant differences in public health insurance enrollment and preventive care use for kindergarten-aged children between counties that

received the outreach intervention treatment from those who did not. However, the findings from the qualitative work in this study may be helpful in implementing other school-based outreach efforts to enroll children in public health insurance. The findings from chapter two indicate that there is a nontrivial positive effect of policy dispersion on children's reading, math, and fine motor skills in kindergarten. Future research in this area should explore the specific mechanisms through which policy governance translates into meaningful differences in children's well-being. The findings from chapter three show that when parents read books, sing songs, and engage in supportive parent-child interactions as early as 9 months of age, this has an important effect on children's reading skills in kindergarten in addition to the effect of maternal education and ability, and family income. These behaviors are important inputs in the development process because they are amenable to policy intervention.

Dedication

I would like to dedicate this dissertation to my father, Walter Marcus, whose support and devotion for me and for his family is unparalleled. I hope that this work is reflective of a small portion of his intelligence, patience, wisdom, grit, and inexhaustible care for my late mother, Frieda Engel Marcus, to whom I also dedicate this work.

Acknowledgements

The work presented in this dissertation would not exist without the help and support of many people. The length of this section is one small indication of my overwhelming and humbling sense of gratitude for the people in my professional life. First and foremost, I would like to express my abundant gratitude for my advisor, Dr. Gary Henry, for his unfailing support of my Ph.D. study and research, for the fantastic opportunities he has provided me with to learn how to conduct rigorous and truly policy-relevant research, for being an exemplar of an applied researcher, and his discerning and thoughtful feedback on all the prior drafts of this dissertation. This is in addition to the continuous support and enthusiasm for my work he has provided over the past five years.

I am also fortunate to have a dissertation committee composed of intelligent and supportive people whose skills are complimentary to one another and who have been unsparingly generous with their time and wisdom for the past five years. I wish to acknowledge and credit Dr. Sudhanshu Handa with helping to shape me from a tree-hugging, save-the-children advocate into a hard-nosed policy wonk and applied econometrician. His unconventional but extraordinarily effective methods for teaching applied economics completely changed the way I think about policy and statistics. Chapter 3 would not exist without his tutelage and encouragement.

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Finally, the study in chapter 1 would not have been possible without the hard work of many people, but principally from the policy entrepreneurship of Dr. Daniel Gitterman who conceived the intervention and who was instrumental in securing the funding for the study. With that said, I am grateful to Dr. Gitterman's guidance not only in this study, but also for encouraging me to focus on state policy governance as the thesis of chapter two. His acumen of all things political—of which there are several in policy and the academy—and the application of this shrewdness in his advising has been truly influential in my progress through the program and into my career.

I want to acknowledge the Graduate School of the University of North Carolina at Chapel Hill for awarding me a Dissertation Completion Fellowship in my final year of doctoral study. The fellowship award made it possible for me to focus solely on the research presented in this dissertation. The overall quality, rigor, and comprehensiveness of the work herein are without a doubt a function of the fellowship opportunity.

I also wish to acknowledge the hard-working and devoted professional staff at the Early Learning Coalition of Alachua County, in Gainesville, Florida. It was my experience at the coalition that motivated me to pursue doctoral training in public policy in order to enact systematic changes for the well-being of young children living in poverty. I am humbled by the inexhaustible passion of these people who help children day-in and day-out, and hope that my work will one day have as great of an impact as theirs has.

As stated above, chapter one is the result of the efforts and research assistance of many people. I wish to recognize Steve Shore, Ania Boer, Laura Brewer, Betty Macon, and India Foy with the North Carolina Pediatric Society Foundation and the Healthy and Ready to Learn initiative for working with me throughout the implementation and evaluation process. I gratefully acknowledge Meera Jagannathan, Andreas Biermann, Kristen DaCanal, Nicole Hensel, Lyle Hendrick, Jill Kite, Michael Little, and Samuel Watson at the Carolina Institute for Public Policy for their research work. I also would like to acknowledge Dr. Chirayath Suchindran at the Biostatistics Department at UNC at Chapel Hill for consultation on the measures used in the study and the North Carolina Division of Medical Assistance for providing the key data for the analyses. Finally, I wish to acknowledge the meticulous budgeting and management work done by Elizabeth D’Amico to support this research.

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Preface

Poverty and early childhood development

Poverty is a significant social problem that poses harmful and often irreversible threats to child development. Child poverty rates have been on the rise for nearly 40 years and is far more prevalent for children in the United States than for those in other industrialized countries (Kamerman & Kahn, 1997; Smeeding, 2005). Forty-six percent of infants and toddlers live in poverty in the U.S., a rate that surpasses adults and senior citizens (Chau, Thampi, & Wight, 2010).

Thirty years of research have established that family income and other measures of socioeconomic status (SES) are associated with cognitive, behavioral and health outcomes in childhood. Poor children do worse on tests of cognitive ability, are more likely to perform poorly in their classes, have higher arrest, retention and school dropout rates, and experience more serious emotional and behavioral problems (Bradley & Corwyn, 2002 provide a comprehensive review of these studies; Brooks-Gunn & Duncan, 1997; Cunha & Heckman, 2007; Holzer, Schanzenbach, Duncan, & Ludwig, 2007; McLoyd, 1998). Both the depth of its causes and the breadth of its consequences make child poverty a concern for people across all political persuasions and academic disciplines.

Moreover, the earlier a child experiences poverty, the worse the outcome; three-year-olds whose parents are professionals have vocabularies that are 50 percent larger than those of children from working-class families, and twice as large as children whose families receive welfare (Hart & Risley, 1995). The experience of poverty and distress during the first five years of life more strongly predict cognitive outcomes than poverty in middle or late childhood (G. J. Duncan, Yeung, Brooks-Gunn, & Smith, 1998), and has detrimental effects on adult earnings (G. J. Duncan, Ziol-Guest, & Kalil, 2010). This is because the child's environment and experiences during this period lay the biological foundation for learning, health and behavior, and greatly influence their life trajectory.

For these reasons, publicly funded intervention programs target families with children ages birth to five to mitigate the consequences of poverty (Brooks-Gunn & Duncan, 1997; Gormley, Gayer, Phillips, & Dawson, 2005; Howes et al., 2008; Shonkoff & Phillips, 2000). The efficacy of early childhood intervention is supported by evidence from education, neuroscience, developmental psychology, and economics that demonstrate the importance of high-quality experiences, activities, interaction and engagement during the first five years of life on children's cognitive and language development (Barnett, 2011; Bowman, Donovan, & Burns, 2000; Hackman & Farah, 2009; Heckman & Masterov, 2007; Magnuson & Waldfogel, 2005; McLoyd, 1998; NICHD Early Child Care Research Network, 2005; Peisner-Feinberg et al., 2001; Sameroff, 2010). This is because early childhood is considered a 'sensitive period' when specific experiences cultivate or inhibit neural connectivity (Hess, 1973; Knudsen, 2004). At birth, the brain is dependent upon interactions, experiences, and environmental stimulation for healthy development, which affect everything from molecules to neurological systems (Als et al., 2004; Dawson, Ashman, & Carver, 2000; Greenough, Black, & Wallace, 1987; Lupien, King, Meaney, & McEwen, 2000; McEwen, 2001). Knudsen and colleagues (2006) summarize the evidence from several studies of animal behavior demonstrating that the early environments in which animals are reared exert powerful influences—both positive and negative—on their temperament, social behavior and cognitive skills.

A developmental stage can also be considered 'critical' if the presence or absence of an experience results in irreversible change (Trachtenberg & Stryker, 2001). Early childhood is a critical period because the brain overproduces synapses during the first two years of life, and experience then determines which connections will persist or deteriorate from lack of use (Greenough & Black, 1992; Singer, 1995). Ergo, experiences later in life are substantially less effective in shaping many behaviors (Knudsen, Heckman, Cameron, & Shonkoff, 2006). For policies that address the consequences of child poverty, timing matters.

Additionally, scholars have illustrated the long-term individual and societal benefits of investing resources in children during early childhood (Barnett, 1995; Berlin, Brooks-Gunn, & Aber, 2001; Campbell, Ramey, Pungello, Sparling, & Miller-Johnson, 2002; G. J. Duncan et al., 2007; Heckman, 2008; Reynolds, Ou, & Topitzes, 2004). Heckman and colleagues show that the returns to investment during early childhood are much higher than later childhood, especially for disadvantaged children, and that it is also necessary to invest later in life to reap the benefits of earlier investments (Cunha & Heckman, 2007; Heckman, 2008). This suggests that policies should invest in children across the life cycle, but should be front-loaded in early childhood, corroborating the neuroscience research showing that stimulating early experiences should be complimented with further stimulating and more sophisticated experiences later in life when higher-level neural circuits are maturing (Fox, Levitt, & Nelson Iii, 2010; Karmarkar & Dan, 2006; Knudsen, 2004).

The powerful influence of the environment during early life on child neurological development presents an unrivaled opportunity for policy action. Altogether, this research illustrates why early childhood policy is the cornerstone of a nation's child and family policy.

Early childhood and family policy research

To be a proficient policy scholar, one must be able to understand the multiple dimensions of the particular policy field and the related research landscape. This includes the field's constituent academic disciplines, of which there are several that are relevant to child policy. As illustrated in the previous section, the study of children and poverty is widespread. Because of this broad interest, it may not be surprising that child policy is not a cohesive or comprehensive policy field. Rather, it is a conglomeration of disparate initiatives and institutions, of assumptions and theories, of interests and investments, and of methods and causal claims. For researchers, this often renders the child development literature to be siloed by academic discipline and constrains interdisciplinary scholarship. It is therefore the task of child *policy* scholars to integrate these perspectives and their respective research in a practical way to understand the mechanisms of intervention and to develop innovative policy solutions.

To be sure, reconciling these approaches is a challenge. Classic child policy analysis is based in economics and political science, and is typically concerned with social and economic outcomes aggregated at the adult-level (Huston, 1991). Psychology and education take a child-centered approach to policy analysis, examining the direct outcomes of policies for children as well as their parents (Huston, 1991). While research in psychology, biology, and economics help to understand the mechanisms that produce child outcomes, sociology and political science describe the broader social and institutional structures that shape family life, including the primary child and family policies. All of these perspectives play a unique role in policy analysis

Bringing together the research from diverse fields also means translating, interpreting and practicing different approaches to research design and methods. Child policy research design can be anything from a randomized experiment, a qualitative study, to a controlled laboratory that examines the genetic and biological components of human development. As a result, the analytic methods can range from bivariate, to correlational and across the full spectrum of econometric approaches.

The goals of policy research are to understand the problems of families, test policy alternatives, and assess interventions. The child policy field requires good descriptive research of what low-income families and children are experiencing, an understanding of the emotional, cognitive and biological development of children, an interdisciplinary understanding of the policy field and the policy intervention mechanisms, and powerful causal designs and research methods to assess the effectiveness of policies and interventions. My goal is to cover multiple dimensions of child policy research in this dissertation.

Causal inference in policy research

Methods for causal inference are critical in determining the effects of policies and interventions especially for child policy. Causal inference is at the core of scientific inquiry and thus engages scholars from many disciplines (Morgan & Winship, 2007; Pearl, 2000). Policy scholars often apply the potential outcomes framework, or counterfactual model, to work towards causality. This framework addresses the fundamental problem of causal inference; each unit either receives the treatment or does not receive the treatment, but we never observe the same unit under both states at a particular time (Holland, 1986). This makes it challenging to determine whether both the treated and untreated groups would have the same potential for a given outcome; their average outcomes can either differ from: 1) the effect of the treatment, 2) differences in the individuals prior to treatment, 3) differences in the reaction to treatment, or 4) some combination of both 2 and 3. Researchers can use different design and statistical strategies to approach these challenges to causality (Shadish, Cook, & Campbell, 2002).

Structural research design features come from a theory of experimentation, whereas statistical modeling and econometric procedures stem from a non-experimental framework that uses observational data to examine economic behaviors and test theory (Shadish, et al., 2002). Research design includes the contemplating, collecting, organizing, and analyzing of data prior to outcome estimation (Rubin, 2005). In terms of design, a quasi-experimental (QE) or observational study are considered experiments that have treatments, outcomes, and units, but assign units to treatment in a way that is non-random (Cook & Campbell, 1979). A QE analysis starts by comparing the potential outcomes of the sample and carefully considering the assignment mechanisms; essentially, researchers conceptualize the QE data as coming from a hypothetical randomized experiment (Rubin, 2008). Therefore, the randomized experiment differs only in degree from QE designs in that in the former we are confident that the causal variable of interest is independent of confounding factors, and in the latter we need to justify this with data and theory (Angrist & Pischke, 2010; Leamer, 1983).

Complimenting the design framework, the study of econometrics revolves around how to generate a good estimate in a given situation (Kennedy, 2008). In contrast to design, econometrics focuses on problems *inherent* in collecting and analyzing observational and QE data to understand relationships, test economic theory and evaluate policies (Wooldridge, 2009). Furthermore, econometricians often criticize the randomized experimental design for its limited generalizability, ethical implications, time constraints, and ability to answer other important questions to social sciences and program evaluation (e.g. mechanisms, selection processes and economic behavior) (Heckman & Smith, 1995). Econometricians have made significant contributions to the treatment effect literature, including techniques such as instrumental variables, structural equations modeling, and propensity scores (Lee, 2005).

There is some contention in the policy evaluation literature on the experimental or design approach vs. the econometric approach (Glazerman, Levy, & Myers, 2003; Heckman & Smith, 1995). It is now well established that while both research design and statistics are critical, design is paramount (Angrist & Pischke, 2010; Rubin, 2008; Shadish & Cook, 1999; Shadish, et al., 2002). Solid statistical analysis alone cannot warrant valid causal inference; they work best after good design features are in place (Shadish, et al., 2002). Nonetheless, it is also true that policy researchers must invariably tackle non-random assignment and require econometric tools to overcome confounding. Thus, this dissertation incorporates both design and econometric techniques.

The dissertation approach

The focus of this dissertation is policy research concerning low-income families with children ages birth to five years. This dissertation is composed of three independent essays. In the following chapters, I demonstrate my command of methods for causal inference by applying both research design and a diverse set of econometric techniques. This is complimented with strong external validity by using data that are representative of children on both the national and state levels, and robust child and family outcomes that cover cognitive, physical, and behavioral measures. I examine different units of treatment;

children, families, schools, counties, and states. These differences allowed me to show my ability to combine and manipulate data from numerous sources and create panel datasets for analysis. Lastly, in line with recommendations from child development and public policy scholars, this dissertation is interdisciplinary; it includes literature, theory, and methods from economics, developmental psychology, political science, public health, education, neuroscience, and sociology.

I have designed these essays so that each paper is an example of a different type of policy research: program evaluation, state policy evaluation, and testing and advancing theory. Each paper shows a particular kind of method, depth, and theoretical motivation, and the analyses address the unique challenges of the research approach. In combination, I believe that all of these components create the foundation for a strong dissertation that meets the requirements of the Doctor of Philosophy degree in Public Policy. In the following chapters I present each of the above papers in turn as independent, stand-alone studies.

Chapter 1 is a program evaluation of a school-based outreach intervention to enroll low-income children in publicly funded health insurance programs in North Carolina. This paper shows my ability to use program evaluation methods with a strong causal design to address selection bias, the primary threat to causality when examining program take-up. This paper also uses mixed-methods and cuts across public health and education. The findings may help to expand our understanding of preventive health care use among low-income families and the role of schools in public health research.

Chapter 2 then expands evaluation to the level of state policy by looking at one particular aspect of state policy governance, policy dispersion, to see if and how it affects children's cognitive and physical development in early childhood. Here I demonstrate my understanding of the endogeneity of policy adoption and address threats to causality with a number of econometric tools. I also show my ability to integrate research from policy management and administration, political science, and early childhood education. This study provides empirical bases for how the governance of state policy influences policy outcomes.

In chapter 3, I use current research in neuroscience and developmental psychology in the context of economic theory to examine the allocation of household resources, including family characteristics and behaviors, during early childhood. I apply the theoretical research to policy by conceptualizing family factors as intervention mechanisms to mitigate the effects of poverty on child development.

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LIST OF ABBREVIATIONS

ECCE	Early child care and education
ECLS-B	Early Childhood Longitudinal Study – Birth Cohort
CCDF	Child care and Development Fund
CDF	Children’s Defense Fund
CDPF	Child development production function
CHIPRA	Children’s Health Insurance Program Reauthorization Act
CMS	Centers for Medicare and Medicaid Services
DID	Difference-in-Differences
DMA	Division of Medical Assistance
FPL	Federal poverty level
HHS	Department of Health and Human Services
HRL	Healthy and Ready to Learn
IDEA	Individuals with Disabilities Education Act
IRT	Item response theory
IVE	Instrumental variables Estimation
KFF	Kaiser Family Foundation
KHA	Kindergarten health assessment
NC	North Carolina
NCATS	Nursing Child Assessment Teaching Scale
NPM	New Public Management
OLS	Ordinary least squares
PCA	Principal components analysis

PCG	Primary caregiver
PRWORA	Personal Responsibility and Work Opportunities Reconciliation Act
QAV	Quantitative assignment variable
RD	Regression discontinuity
SCHIP	State Children’s Health Insurance Program
SD	Standard deviation
TANF	Temporary Assistance to Needy Families
TBT	Two-bags task
VAM	Value-added model

CHAPTER 1. THE EFFECTS OF A SCHOOL-BASED PUBLIC HEALTH INSURANCE OUTREACH PROGRAM ON HEALTH CARE USE IN KINDERGARTEN-AGED CHILDREN

Introduction

Public health insurance is a critical component of child and family policy. Presently, over eight million children in the U.S. are uninsured while health care costs continue to rise and families struggle to find affordable care (Kaiser Family Foundation (KFF) 2011). Medicaid and the State Children's Health Insurance Program (SCHIP) are the largest government interventions in child health insurance coverage, and account for a significant share of health care spending overall. Together, these two programs have successfully increased rates of child insurance, particularly since the enactment of SCHIP in 1997 and the subsequent expansion income eligibility to cover more low-income working families though the CHIP Reauthorization Act (CHIPRA) in 2009. However, the current uninsured rate among children from birth to age 18 remains stagnant—around seven percent—as policymakers struggle to figure out how to successfully enroll the millions of eligible yet uninsured children (R. A. Cohen & Martinez, 2012).

Government-sponsored health insurance is especially important given the current economic recession as furloughs, layoffs, and steep benefit cuts reduce the number of families covered by employer-sponsored health insurance (Ross & Marks, 2009). The economy notwithstanding, one of the most important justifications for public intervention in health insurance is that children who are uninsured do not receive routine preventive care. This is not only detrimental to child well-being in the short- and long-terms, but also imposes significant costs for both families and society at-large. Yet it is unclear that providing health insurance to uninsured children affects whether parents actually *access* preventive care for their children.

If there is a relationship between insurance coverage and receipt of health care, the 8.3 million uninsured children in the U.S. are an important policy concern (Kaiser Family Foundation, 2011). When children do not receive routine preventive care, they have worse health outcomes overall including lower rates of vaccination, reduced likelihood of identifying problems that require early interventions, and more inappropriate use of emergency department services (Kenney, Marton, Klein, Pelletier, & Talbert, 2011). This not only affects their ability to focus and attend school, it also affects their educational and labor market outcomes in the future (Currie, 2009; Thies, 1999). The negative externalities of poor child health are also costly for society because uninsured children have more expensive health care, of which their families can only afford to pay a portion of; the rest passed on to taxpayers (North Carolina Institute of Medicine (NCIOM), 2009). This is in addition to the public health costs from illness due to missed vaccinations (Zhou et al., 2005).

Regardless of whether there is a relationship between health insurance coverage and health care access, enrolling uninsured children is the critical first step in intervention. In an effort to further increase enrollment, the Centers for Medicare and Medicaid Services (CMS) offered CHIPRA-Cycle I outreach and enrollment grants to states to develop local outreach initiatives that identify and enroll eligible children. North Carolina received a CHIPRA I grant in 2009 to implement the *Healthy and Ready to Learn* (HRL) initiative. The HRL initiative is a targeted, two-year, school-based SCHIP and Medicaid outreach program whose goal was to identify and enroll eligible and uninsured children entering kindergarten in the

2010 and 2011 school years. Sixteen counties in NC were selected for the intervention based on an index of economic need. School personnel in treatment counties were trained on program requirements and how to identify potentially eligible children using the Kindergarten Health Assessment form (KHA). The KHA is a required document for all children entering kindergarten that contains important health information including insurance status and other key health indicators that are valuable to educational and medical professionals, as well as policymakers.

The goals of this study are threefold. We assess: 1) whether the HRL intervention was effective at increasing Medicaid and SCHIP enrollment rates for kindergarten-aged children; 2) whether HRL increased preventive care use in SCHIP and Medicaid for kindergarten-aged children; and 3) the mechanisms through which school staff were able to identify children who were eligible but uninsured. We address the potential for selection bias in program enrollment and preventive care use using a rigorous quasi-experimental research design—the regression discontinuity (RD)—with statewide administrative public health insurance data. In addition, we use qualitative methods to determine the most successful strategies used by school staff to identify children and assist families in enrolling in public health insurance. Using mixed-methodology, this study adds to the public health intervention and evaluation literature concerned with the role of schools in child health and the extent to which access to public health insurance changes the health behaviors of families with young children.

Background and literature

Benefits and costs of health insurance coverage for children

The motivation behind public health insurance for children is to improve child well-being by increasing access to and use of preventive care, providing emergency coverage, and decreasing the costs of sickness without coverage (Kenney, et al., 2011; C. D. Perry & Kenney, 2007). Uninsured children have less access to health care services, more serious health problems, are more likely to forgo or not receive essential health care, and also use more expensive medical services than children in public or private insurance programs (Arroyo, Ewen Wang, Saynina, Bhattacharya, & Wise, 2012; Byck, 2000; Mannix, Chiang, & Stack, 2012; Newacheck, Hughes, & Stoddard, 1996; Newacheck, Stoddard, Hughes, & Pearl, 1998; Ziller, Lenardson, & Coburn, 2012). In many ways, lack of coverage presents threats to children's development, family well-being, community and school health, and to society at-large.

Lack of insurance is a problem that disproportionally affects children in low-income and working-poor families (Angier, DeVoe, Tillotson, Wallace, & Gold, 2012; R. A. Cohen & Martinez, 2012). Currently, almost three-quarters (72%) of the 8.3 million uninsured children in the U.S. live in low-income families, and the majority of uninsured children (65%) live in families with at least one full-time worker (Kaiser Family Foundation, 2011). This is worrisome for policies concerning educational equity because some research suggests that child health may be a causal mechanism through which socioeconomic status influences educational attainment and academic achievement, further exacerbating achievement gaps (Case, Fertig, & Paxson, 2005; Heckman, 2008), especially for black and Latino children (Crosnoe, 2006). Poor child health affects not only children's current ability by reducing school attendance, concentration and participation, but poor health is also bad for children's future educational, health, and labor market outcomes (Case, et al., 2005; Currie, 2009; Thies, 1999).

High rates of uninsured children create other significant costs for society. The uninsured forego care and exacerbate certain health conditions putting them in emergency care (Arroyo, et al., 2012; Hadley, 2007; Wisk & Witt, 2012). Indeed, one-quarter (23%) of uninsured children have delayed or postponed care because of cost relative to 3% of insured children (Kaiser Family Foundation, 2011). They also pay for one-third of their care out of pocket, with the remainder of the costs covered by higher taxes and insurance premiums (NCIOM, 2009). In North Carolina, individuals pay an average of $438 more a year, with families paying an extra $1,130 per year on health insurance premiums to help cover the costs of uncompensated care for the uninsured (Stoll, 2005).

In terms of policy levers, public health insurance is an important protective factor for children because it can encourage routine preventive care. Well-child visits and preventive care are associated with improved child health and reductions in avoidable hospital visits and dental costs later in life (Hakim & Bye, 2001; Savage, Lee, Kotch, & Vann, 2004). The American Academy of Pediatrics recommends that children ages 3-21 receive annual well-child visits (Hagan, Haw, & Duncan, 2008), though national data show that many children do not receive this care (Selden, 2006). This is troublesome because children who do not receive an adequate number of well-child visits are less likely to be current on their immunizations and are more likely to have avoidable hospitalizations, both of which have meaningful public health implications (Clark, Freed, Pathman, & Schectman, 1999; Hakim & Bye, 2001). The public benefits of vaccination alone are significant. One study estimates that every dollar spent on the routine childhood immunization schedule saves more than $5 in direct costs and approximately $11 in additional costs to society due to contagion (Zhou, et al., 2005).

Routine visits are also important for child and family well-being in the long term. During these visits, physicians assess biomedical health, development, family functioning, and identify potential problems (Dinkevich & Ozuah, 2002). This is critical for the timely detection of health, developmental, and behavioral problems that may require early intervention. A physician's early diagnosis has the potential to reduce mortality, morbidity, and disability and enable children to lead healthier and more productive lives (Halfon & Olson, 2004; Shonkoff & Phillips, 2000). Well-child visits also give physicians the opportunity to provide anticipatory guidance, which is practical and developmentally appropriate information about children's health such as injury prevention, nutrition, and immunizations (Dinkevich & Ozuah, 2002; Hagan, et al., 2008).

There is a clear policy rationale for public health insurance based on the benefits for children, families, and the public. Still, the connection between the policy lever of public health insurance and child well-being is no small step. The implementation of Medicaid and SCHIP involves policy actors at the federal, state, and local levels to successfully translate the funding and administration of these policies to the recruitment and enrollment of eligible children before public insurance can increase the use of preventive care.

Medicaid and the State Children's Health Insurance Program

Government commitment to public health insurance programs for children began in 1965 with Medicaid for poor children (Lewit, Bennett, & Behrman, 2003). Medicaid requires states to provide health insurance coverage to children age six and under whose families are at 133% of the federal poverty level (FPL) or below, and for children ages six to

18 whose families are at 100% of the FPL or below (HHS-CMS, 2009). Federal investment increased in 1997 when Congress authorized almost $40 billion for the State Children's Health Insurance Program (SCHIP), the largest single expansion of health insurance coverage for children in over 30 years (HHS-CMS, 2009). Within federal guidelines, each state determines the design of its CHIP program including eligibility parameters, benefit packages, payment levels for coverage, and administrative procedures (HHS-CMS, 2009). The federal government matches state funding for both programs but unlike Medicaid, states receive a capped allotment of CHIP funds.

From 1998 to 2007, SCHIP allowed states to provide health insurance to children from low-income, working families earning between 100 to 200 percent of the FPL who were not covered by Medicaid (General Accounting Office, 2000b). By 2003, the uninsured rate among children dropped below 12.5, the lowest since 1977, and the number of eligible but uninsured children fell 25% between 2001 and 2005 (Hudson & Selden, 2007). Rates of coverage continued to increase through 2005, and some studies indicate that the expansion in eligibility reduced the uninsured rate among children (Hudson & Selden, 2007). The increased outreach efforts under SCHIP are also associated with the spikes in enrollment during this period (Duderstadt, Hughes, Soobader, & Newacheck, 2006).

Despite the increased coverage since CHIP enactment in 1997, close to two-thirds of all uninsured children appeared to be eligible for Medicaid or CHIP in 2008, but were not enrolled (Kenney, Cook, & Dubay, 2009). Then the Children's Health Insurance Program Reauthorization Act (CHIPRA) of 2009 and the Patient Protection and Affordable Care Act of 2010 included provisions to further increase children's health insurance coverage through 2013 with a total four-year allotment of nearly $70 billion (Horner, Guyer, Mann, & Alker, 2009; Kaiser Family Foundation, 2011). A recent meta-analysis of Medicaid and CHIP expansions shows clear gains in public health insurance coverage and declines in uninsured among children (Howell & Kenney, 2012).

Today, Medicaid and SCHIP together cover over half (59%) of low-income children, bringing the national rate of children insured to over ninety percent (Kaiser Family Foundation, 2011). This coverage is especially important in the face of increased unemployment because these programs offset most of the decline in families' employer-sponsored insurance (Dorn, Bowen, Holahan, & Williams, 2008; Ross & Marks, 2009). Yet the question still remains as to whether increasing enrollment and opening up eligibility for public insurance programs will increase preventive care use for children.

The effects of Medicaid and SCHIP on child health

Before the enactment of SCHIP, studies from Pennsylvania (Lave et al., 1998), New York (Szilagyi et al., 2000), and Florida (Shenkman et al., 1997) found that children who were enrolled in a state insurance program for low-income children had significant improvement in health care access, utilization, and quality of care (Szilagyi et al., 2004). One study showed that children enrolled in Medicaid or SCHIP were more likely than full-year-uninsured and part-year-uninsured children to have had a preventive visit at a doctor's office or clinic in the past 12 months (C. D. Perry & Kenney, 2007). Children who were uninsured for part-year were more likely to have had a preventive visit than children who were uninsured for the full year, though only 41% of publicly-insured children had a preventive care visit. Evaluation of the New York SCHIP program also indicates that once children were enrolled they were more likely to receive health care from a primary care provider (Szilagyi, et al., 2004). In North Carolina, initial SCHIP evaluations showed improved access to care for enrollees as well (Slifkin, Freeman, & Silberman, 2002). Analyses using more nationally representative data indicate that children with continuous public coverage had significantly better access and utilization of health care when compared with eligible but uninsured children, and had equivalent or better access and utilization compared to children with private coverage (Duderstadt, et al., 2006; Howell & Kenney, 2012; Szilagyi, et al., 2004).

Still, there is significant variation across states with respect to SCHIP enrollment and retention policies (Ross & Marks, 2009) and participation rates (Kenney, Lynch, Cook, & Phong, 2010), and variation in national estimates of Medicaid and SCHIP children who receive a well-child visit (Kenney, et al., 2011). Causal analyses are critical to substantiate or refute the correlational evidence because selection bias and confounding by unobserved health factors are central issues in studies on public health insurance (Hadley, 2003). The strongest evidence to date on the effectiveness of public health insurance programs comes from the recent evaluation of the Oregon Health Insurance Experiment. Adults were randomized through a lottery system into Medicaid and after one year, the treatment group had substantively and statistically significantly higher health care utilization (including primary and preventive care as well as hospitalizations), lower out-of-pocket medical expenditures and medical debt and better self-reported physical and mental health than the control group (Finkelstein et al., 2011).

While stronger causal research methods are difficult to implement in this area, they can provide important information for health policymakers about the private and public benefits of government-sponsored health insurance. Health insurance promotion campaigns and outreach initiatives can provide a good opportunity to understand the relationship between health insurance and health care access, especially when evaluated using a strong research design. In the following sections, we describe the details of one such initiative and the research evaluation approach we use to study the relationship between outreach, enrollment, and preventive care use with respect to public health insurance programs for children.

CHIPRA outreach and the NC Healthy and Ready to Learn initiative

Not long after the initial launch of SCHIP, it became clear that different outreach strategies were required to reach the various sub-populations of eligible children (I. Hill, 2002). CHIPRA included outreach and enrollment grants and bonus payments to states for adopting identified enrollment and retention strategies or increasing enrollment beyond expected targets (Horner, et al., 2009). By April of 2010, the federal government had awarded $50 million in outreach grants. These grants are important for enrolling uninsured children because initial evidence from national SCHIP evaluations estimate that one-third of eligible but unenrolled children have not enrolled because of knowledge gaps (Dubay, Kenney, & Haley, 2002). Studies suggest that Medicaid or SCHIP-eligible families could benefit from targeted engagement strategies linking them with consistent and appropriate sources of pediatric health care (Cullen, Matejkowski, Marcus, & Solomon, 2010), and most states promoted both programs jointly to increase enrollment (M. J. Perry, 2003). All of these factors led to the development of the outreach initiative evaluated in the present study.

North Carolina (NC) offers children's health insurance through the SCHIP program *Health Choice* for Children, for children ages six-18 whose families' incomes fall between 100 and 200 percent of the FPL, and through the Medicaid program *Health Check* to children ages five and under with incomes below 200 percent of the FPL. By 2007, these two programs insured nearly 800,000 children (Task Force for a Healthier Carolina, 2007). CHIPRA increased North Carolina's 2009 SCHIP allotments over the previous law by 81 percent (Peterson, 2009). However, in 2009, three out of every five uninsured NC children were eligible for, but were not enrolled in one of the two programs (NCIOM, 2009). This disparity stemmed from both insufficient outreach efforts and a need to simplify the enrollment and renewal processes (Task Force for a Healthier Carolina, 2007).

In October 2009, North Carolina received a $678,210 CHIPRA Cycle I Outreach and Enrollment grant for the initiative *Healthy and Ready to Learn* (HRL). In line with the joint policy initiative by the National Association of the State Boards of Education and the Centers for Disease Control, HRL focuses on schools as a source of health information and a context to develop fit and healthy children who are 'ready to learn' (2000). School-linked initiatives are important because children enter schools with myriad social, health, and developmental issues (Konrad, 1996). The HRL intervention was a targeted, school-based SCHIP and Medicaid outreach and enrollment initiative for identifying and enrolling eligible and uninsured children entering kindergarten in NC's 16 highest-need counties, led by the North Carolina Pediatric Society Foundation (NCPSF). The HRL goals were to: 1) increase enrollment of eligible but uninsured kindergarten-aged children in NC high-need counties; 2) improve efforts for outreach and enrollment by identifying uninsured children using the Kindergarten Health Assessment (KHA) information; 3) establish strong relationships with school nurses and School Health Advisory Councils; and 4) identify successful strategies for school-based outreach programs to extend outreach and enrollment efforts across the state.

HRL implementation and evaluation

In the first year (2009-10), 16 counties were selected as intervention sites based on an economic need index that included 278 elementary schools in 22 Local Education Agencies (LEA) or districts. The University of North Carolina Sheps Center for Health Services Research developed the quantitative need index used to determine the counties who received the intervention. This index incorporated county-level data on two economics-related measures (percent of children ages birth to 18 in poverty and the unemployment rate for April/May 2009) as well as the number of children who could potentially be reached by the intervention (number of children aged six to eight). The index measure values by county are displayed in Appendix A.

Each LEA in the treated counties received $3000 to use for program purposes at their own discretion. In year two, the intervention was extended to an additional 32 counties who were also selected based on the ranking of their index score. The second group had greater geographic spread and fewer HRL staff members per county (1:8 in the pilot group, 1:16 in the second group). Figure 1 shows a map of the intervention counties by year.

The primary component of the initiative was a series of regional trainings in the selected pilot school districts for local school-based personnel, primarily school nurses and administrative staff. Under the NC Health Assessment Law (G. S. 130A-440), every child entering kindergarten in public schools must receive a health assessment by a medical provider no more than 12 months prior to school entry.). The KHA is a required document for all children entering kindergarten that contains important health assessment data regarding illnesses, developmental and behavioral concerns, vision/hearing screening results, and BMI; whether or not the child receives regular health care and the medical home for care. Nurses must systematically review KHAs to identify the health needs of children entering their school. The HRL initiative highlighted the section of the KHA form where parents indicate whether the child has Medicaid, private insurance/HMO, or no insurance, outlined in red in Figure 2. Nurses and staff could then identify uninsured children and refer their families to local partners for potential Medicaid/SCHIP enrollment.

HRL staff conducted a similar web-based training with physicians, nurses and other health care providers in pilot counties to encourage providers to talk with families about insurance coverage during the well-child visit for the purposes of filling out the KHA form. HRL also involved continuous community-based outreach throughout the study period. This included attending community events, providing outreach materials in various languages, assisting schools in their outreach programs and troubleshooting, and contacting local organizations and community leaders to help inform families about SCHIP and Medicaid.

An additional goal of the HRL program was to increase the completion rate of the parent report items on the top of the KHA form (the grey box at the top of Figure 1.2). Because the health care provider fills out most of the form, there is historically low completion of the parent section. However full completion was essential to the eligibility identification strategy of HRL—using the health insurance status item on the KHA (marked in red in Figure 1.2). A statewide probability sample of KHA forms collected by the NC Department of Health and Human Services, School Health Division in 2008 confirmed the high rate of missingness on these forms (North Carolina Department of Health and Human Services & Devision, 2009). Therefore, teachers and other school administrative staff were instructed to check the parent report section of the KHA form before accepting it from the parent or child, and returning it to them if incomplete.

Present study

This study is a comprehensive evaluation of NC's HRL initiative. We assess whether the HRL intervention was effective at increasing Medicaid and SCHIP enrollment, and assess whether HRL increased preventive care use (i.e. well-child exams) in SCHIP and Medicaid for the target population in treated counties. Our primary treatment effect identification strategy is a Regression Discontinuity design (RD) estimator, taking advantage of the quantitative index measure used to assign counties to HRL treatment. We use statewide administrative data from the NC Department of Medical Assistance (DMA) in conjunction with other county-level data in our analyses, and also test for the robustness of our RD estimator using multiple model specifications and estimation strategies.

In addition to the quantitative analyses that test for the overall effect of HRL, we also wanted to assess best practices in school-based and community outreach efforts and to identify any other hidden treatments occurring in HRL counties. Therefore we conducted focus groups and key informant interviews with school nurses in the 16 HRL pilot counties. In combination, this study adds to the public health intervention and evaluation literature concerned with the role of schools in child health and the extent to which access to public health insurance changes the health behaviors of families with young children.

Data

Kindergarten Health Assessment (KHA) forms

Every child entering kindergarten in NC public schools must receive a health assessment by a medical provider documented using the KHA. Therefore, the KHA form contains important health assessment data. Currently, this form can only be completed in hard-copy. The KHA is not scannable into an electronic database because of the layout of form items, and must be manually coded for analysis. Therefore, each elementary school in the 16 pilot counties were required to photocopy the front-side of the KHA form (Figure 2) for the first intervention year, and to send these copies to the evaluation team. Trained undergraduate research assistants manually coded the forms into an electronic database using Qualtrics Survey Software. The resulting dataset includes the child's name and birthdate, health insurance status, and more than 60 coded child health items. The full sample for the KHA data is 15,397 kindergarten children in 12 of the 16 HRL pilot counties.[1] Sample proportions for a selected set of items from the KHA are listed in Table 1.2.

Medicaid and SCHIP administrative dataset

We calculated county-level health insurance enrollment and preventive care usage from the Medicaid and SCHIP claim data for all counties in NC. These are comprehensive administrative data collected by the DMA and include all claims made by children living in NC who were kindergarten aged in the 2007-08 through 2010-11 school years. The data contain three cohorts of kindergarteners who were enrolled in Medicaid or SCHIP (one year prior to intervention and two intervention years). The raw data were in long format where each observation represents a unique claim for a child, with approximately nine million observations in total. In the first treatment year, there were approximately 134,000 kindergarten-aged children enrolled in Medicaid or SCHIP. Variables include name, birthdate, county of residence, claim type and the total amount paid for each claim. Claim types include dental, drug and well-child health screenings. We therefore use the presence of a well-child exam claim as our measure of preventive care use, and refer to it as such.

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[1] Due to funding and time constraints, KHAs were coded only for a subsample of the 16 pilot counties.
[2] Any child identified as a 2010 kindergartener based on age that appeared in the file in 2011 was included in the 2011 enrollment counts to allow for the lag period that may occur between exposure to HRL in kindergarten

We identified children in the DMA file as a member of the 2008-09, 2009-10, or 2010-11 kindergarten cohorts if they were five years of age on or before July 1st of one of the above academic years, including only one observation per child to represent enrollment.[2] Similarly, we identified the number of well-child exam claims using the claim type variable for Health check/screening, including only one observation per child. These data were then aggregated to the county-level by year. Each observation in the analysis dataset then represented a county's enrollment rate, well-child claim rate, HRL status and values of the control variables in a given year, and thus includes 300 observations (100 counties * 3 years).

Note that this sample represents every county in NC, and the KHA sample described above is a subset of the HRL pilot counties. Therefore the latter represents the NC counties with the highest economic need (as measured by the index) and are not representative of all counties in NC.

Control and outcome variables

County-level covariates were extracted from numerous data sources to use as controls in the outcome analysis and are listed in Table 1.1. Parts of our dependent variables were constructed using the DMA administrative claims data as described above. These data allowed us to determine the total number of children enrolled and number of children who received a well-child exam in each county, but they do not indicate the *proportion* of income- and age-eligible children by county that these numbers represent. Therefore, we needed to conduct some additional calculations incorporating other data in order to develop enrollment and well-child exam *rates* to use as dependent variables. Principally, this involved

[2] Any child identified as a 2010 kindergartener based on age that appeared in the file in 2011 was included in the 2011 enrollment counts to allow for the lag period that may occur between exposure to HRL in kindergarten and completing enrollment in SCHIP or Medicaid. These children were only included if they did not appear in the claims data in 2010.

estimating an appropriate *denominator*—the total number of children who are income- and age-eligible for Medicaid and SCHIP by county.

The study target population was kindergarten-aged children, so we defined the age-eligible population as the total number of five-year-old children living in the county from the 2010 Census. We adjusted this number for survival with demographic calculations[3] using Sprague multipliers based on county- and state-level statistics. We then adjusted this number for poverty using the 2011 Census American Community Survey (ACS) *estimates* of the number of children ages 0-18 living at or below 200% of the FPL in each county (i.e. the SCHIP/Medicaid eligibility limit) to determine the proportion of children who were income-eligible (U.S. Census Bureau, 2012). These estimates became our denominators for both the enrollment and well-child exam outcome measures so that they respectively represent the proportion of age- and income-eligible children enrolled, and those who received a well-child exam during the intervention period. The variables involved in this calculation, mean values, and data sources are listed in Table 1.1.

The mean values of these estimates for enrollment and well-child exam rates are displayed by year in Table 1.3. Note that a key weakness of our dependent variable calculation is that many of the calculations are above one, which is seemingly unreasonable for measures of rates. This is because the 2011 ACS numbers that we used to represent the proportion of children living in poverty are *estimated* based on the 2010 Census and therefore are not 'true' population parameters. We suspect that the 2011 ACS estimates for county-level poverty *underestimate* the true number of children living below 200% FPL and are thereby eligible for SCHIP or Medicaid, in part because the economic recession likely caused

[3] Dr. Suchindran, demographer and Professor of Biostatistics at UNC, provided consultation to generate these estimates.

drastic changes in families' poverty status during this time. Because of this, it appears as though there are more income- and age-eligible children enrolled than there are income- and age-eligible children in the county (i.e. number of kids enrolled>number five year olds who are below 200% FPL). As a result, our enrollment and well-child exam rates are significantly above 100 percent because the estimated denominator we use in our calculations is in all likelihood lower than the 'true' denominator. Therefore, our calculations provide a relative measure of differences in rates between the groups, but do not represent true or absolute rates.

Focus Groups and Key Informant Interviews

We conducted four focus groups and five key informant interviews across the HRL regions. We collected these data to: assess best practices in school-based and community outreach efforts, document the specific activities involved in the implementation of the HRL intervention, assess the extent to which participants felt that the HRL intervention activities helped to accomplish the stated goals of HRL, and to identify any other hidden treatments that may threaten the validity of the effect estimates. Focus group participants and key-informants were recruited from elementary schools in the HRL pilot counties during year two (16 counties). The HRL program coordinators (NCPSF staff) provided recommendations for potential participants based on their involvement with HRL. Participants are primarily school nurses and administrative staff. We conducted an additional focus group with NCPSF HRL program staff. All participants were given the opportunity to review and sign a consent form describing the purpose of the study and to decline from participation. Participants were not offered any other compensation for their time aside from the lunches provided during the focus group sessions. The UNC-Institutional Review Board approved this research in April 2011 (IRB #11-0564).

Methods

Descriptive Analysis

We calculate 2010 mean and standard deviation values for each county covariate, and the variables used to compose our outcomes, and sample proportions for a selected number of child health characteristics from the 2010 KHA dataset. We present our estimated dependent variables by year and HRL treatment status. We also compare the rates of missingness for the parent report items on the KHA form between the HRL KHA sample (2010) and the statewide probability sample data collected in 2008 to detect whether the HRL efforts improved item completion.

Regression Discontinuity Design

Selection bias is the primary challenge to detecting causal treatment effects when the treatment outcome is program participation or enrollment. In the present study, both treatment and outcomes are at the county-level. Selection bias is possible if unobserved county-level characteristics influence the county's willingness to implement a health insurance outreach program like HRL. For example, counties with worse child outcomes may be more likely to participate, or counties that are not as efficacious at enrolling children in public health insurance may be less likely to participate. The former would deflate the effect of the HRL program, while the latter would inflate the effect.

The impact analysis for causal estimates of the HRL treatment effect will use a Regression Discontinuity (RD) design to address confounding from selection bias. This method will exploit the fact that HRL treatment counties were selected using an economic need index. The primary condition for unbiased causal effects with an RD analysis is the use of a quantitative assignment variable (QAV) and a designated cutoff score or value to determine treatment status (Imbens & Lemieux, 2008; Shadish, et al., 2002). This means that with an RD the probability of receiving treatment must change discontinuously at the cutoff as a function of the QAV (Van Der Klaauw, 2008). This is the key advantage of the RD; the researcher can capitalize on completely known and perfectly measured selection, and thus perfectly *model* selection by conditioning on the value of the QAV in the outcome analyses (Shadish, et al., 2002). If the assignment variable is a deterministic function of assignment to treatment, this is considered a 'sharp discontinuity' (Van Der Klaauw, 2008). In the current study, the index of economic need used to select HRL counties is a perfect predictor of a county's treatment status; no county assigned to treatment did not receive treatment and no county assigned to the control condition received treatment. Therefore, our analysis is a sharp RD. The QAV used for HRL has four unique values above and below the cutoff, meeting minimum requirement for valid identification in RD (Schochet et al., 2010).

Though RD designs are not as strong as randomized experiments, they are considered more credible than estimates from other nonexperimental designs (Reichardt & Henry, 2012). This is because in a randomized experiment, differences between the treatment and control groups are random; in RD, the differences are non-random but observed, if the discontinuity is sharp, so you must control for the QAV in addition to other covariates in proper functional form to avoid bias. A disadvantage is that one must extrapolate the regression line from observed data across treatment conditions (i.e. the discontinuity point) to detect changes in the treatment effect along different values of the QAV (Morgan &

Winship, 2007; Reichardt & Henry, 2012). This is because there is no common support or overlap due to the strict treatment decision rule at the cutoff. No unit with a given QAV value—the determination of treatment—can be on both sides of the cutoff.

In addition to the use of a QAV to assign treatment conditions, the research must also meet the other specific assumptions of the RD model. One model assumption is local conditional independence; close to the threshold, all variables measured prior to assignment are independent given treatment status (Van Der Klaauw, 2008). The individuals just above and below the cutoff are comparable in terms of the QAV and are assumed to have similar average potential outcomes. As a result, the treatment effect identified through the discontinuity at the cutoff compares the average outcomes *only* for those with values just above and below the cutoff and must be interpreted conditionally; this is known as the local continuity assumption (Van Der Klaauw, 2008).

Because of this assumption, it is critical for the analyst to check for RD-specific robustness by examining the appropriate 'bandwidth.' This involves an analysis of restricted samples of observations clustered around the cutoff within a specified range of the QAV (Schochet, et al., 2010). This reduces the effect of data points further way from the cutoff which have decreasingly comparable potential outcomes, and reduces misspecification bias (Van Der Klaauw, 2008). The intuition behind this procedure is that the units close to the cutoff are likely to differ only on exposure to the treatment but those further from the cutoff may differ in additional ways. When bandwidth decreases, there is a tradeoff between sample size and reduction in noise by eliminating values further from the cutoff point that may not be comparable. Therefore, we test three different bandwidths in our RD analyses.

These bandwidths restrict the sample to those counties whose index scores are +/- 4, 3, and 2 QAV units from the designated cutoff value of 19, where the full index ranges from 6-23.[4]

Another unique feature of the design is that the assignment variable can be associated with the dependent variable. This is because the association between the QAV and the outcome is assumed to be continuous or smooth at the cutoff and therefore can be modeled perfectly, so a discontinuity of the outcome at the cutoff point is evidence of a causal effect of the treatment (Imbens & Lemieux, 2008). The researcher is essentially estimating two different regression functions—one for the group below the cutoff and one for the group above—and the treatment effect is the difference of the two regression functions at the cutoff point. Aptly named, a discontinuity at the mean and/or slope at the cutoff score is the identification strategy of the RD design (Shadish, et al., 2002). While in the randomized experiment the treatment effects are inferred by comparing the mean outcomes between the treatment and control, the RD compares the intercepts and slopes of these two regression lines (Shadish, et al., 2002).

Because the QAV[5] may be correlated with the outcome variable in RD—as it is for the HRL intervention—this renders the assignment mechanism nonrandom, which can confound the treatment effect estimate (Van Der Klaauw, 2008). This makes the estimator less precise and has lower power than the randomized experiment because in randomized experiment the treatment dummy variable is not correlated with any covariates (Reichardt & Henry, 2012). Therefore, using additional controls for other observable characteristics helps

[4] We were unable to assess optimal bandwidth using the Imbens and Kalyanaraman (2009) formula that minimizes mean-squared error because our QAV is composed of discrete numbers with only a limited number of treated units (counties), providing insufficient variation to reliably determine bandwidth using this method.

[5] It is important to note that the QAV is not used to measure any qualities of the units under treatment or serve as a covariate; its sole purpose is to measure how participants enter the treatment and control conditions, and thus contain no error for this function when assignment to treatment is sharp (Shadish, et al., 2002).

to increase power, eliminate any other sample biases, and improve the precision of the treatment estimate especially when these covariates affect the outcome (Imbens & Lemieux, 2008; Van Der Klaauw, 2008). Therefore, we include several county-level characteristics related to health care access and economic need in our specifications, listed in Table 1.1.

The other RD model assumptions are: (1) no other changes at the cutoff, (2) treatment did occur, (3) no hidden treatments and (4) plausible mechanisms link the treatment to outcomes (Shadish, et al., 2002). Assumptions two and four are plausible because of the observed implementation of HRL and the literature described in the previous section. The index used for selecting counties into HRL was not publicly distributed, nor is it a natural boundary for other programs or policies occurring in NC during the study period, making assumption one plausible as well. Assumption three is addressed with the qualitative work (focus groups and interviews) conducted in the intervention counties.

One must also to test for sensitivity and robustness with RD analyses. First, the relationship between the assignment variable and the outcome must be modeled correctly to avoid bias in the treatment effect (Imbens & Lemieux, 2008; Reichardt & Henry, 2012; Schochet, et al., 2010; Van Der Klaauw, 2008). We use graphical analyses plotting the relationship between the outcome scores and the assignment variable to model curvilinearity and assess the number of higher order polynomial terms (Reichardt & Henry, 2012; Schochet, et al., 2010). This can also help to determine the appropriate bandwidth. Secondly, we interact the QAV with treatment status to test whether HRL has differential treatment effects for counties at varying levels of the QAV (i.e. different slope for the treatment group). In addition, we ran each analysis separately by year in our specification testing to detect any other year-specific issues with the specification. We show our model specifications in detail in the following section.

Model specifications

We estimated the effect of HRL using three types of analyses[6] and check for robustness of the treatment effect for both enrollment and claims outcomes: 1) standard RD that separates and pools the two kindergarten cohorts under treatment; 2) a 'Difference-in-Differences' (DID) model that captures changes from the pre-treatment period using the 2009 scores as a baseline for comparison; 3) a 'Value-Added' or gain RD model (VAM-RD) where the county's lagged dependent variable (2009) is included as a covariate to analyze 'gain' or change in levels from the prior year. All analyses were estimated with Stata 12 (StataCorp., 2011).

1. ***Standard RD models.*** In the basic RD model, we pool both of the treated cohorts and test for a discontinuity at the assignment cutoff and include a dummy variable for the second year (2011) to capture any exogenous shocks, and cluster the standard errors at the county-level. Pooling is appropriate in this instance because it is plausible that the two kindergarten cohorts are independent of one another. For each RD model, the first specification tests only for a discontinuity at the cutoff point (i.e., intercept shift) with the term $\beta_T T$, shown in (1). The second specification tests for differences in slopes and potential heterogeneity of treatment effects along different values of the QAV by interacting $\beta_{Q_1}(Q_i - Q)$ with the treatment indicator, shown in (2).

(1) $Y_{ijk} = \alpha + \beta_T T + \beta_Q (Q_i - Q) + \beta_{Q^2} (Q_i - Q)^2 + Z_{ij} + \beta\, 2011 + e$

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[6] We also attempted to estimate fit a nonparametric RD with the user-written *rd* command for Stata (Nichols, 2011). However, because our QAV is composed of discrete numbers in a small range above and below the cutoff, we did not have sufficient variation to identify a nonparametric RD estimator.

(2) $Y_{ijk} = \alpha + \beta_T T + \beta_Q(Q_i - Q) + \beta_{Q_1^2}(Q_i - Q)^2 + \beta_{TQ}T(Q_i - Q) + Z_{ij} + \beta\, 2011 + e$

Where Y represents the dependent variable indexed by county (i), school year (j), and type (k)(i.e. enrollment or claims), Q is the cutoff value for the QAV in year two,[7] Q_i represents the county-specific QAV value, T represents the HRL treatment condition, Z represents the set of county-level covariates by year[8] displayed in Table 1.1, 2011 represents last (second) treatment year, and β_{Q^2} represents a squared term of $(Q_i - Q)$ based on the fit of the data in graphical analyses. Note that the counties that were treated in year one are also in the year two treatment.

Falsification tests. In order to further strengthen the internal validity of the RD, we conduct falsification tests using the same RD specification indicated in (1) and (2) with 2009 data to check for a spurious relationship between the treatment and the outcome. This involves a regression of 2009 enrollment rates and well-child exam claims on the HRL treatment variable. If the HRL coefficients are non-significant, this suggests that the treatment effect from the outcome estimation is robust to the RD specification and estimation procedure (Van Der Klaauw, 2008).

2. *Difference-in-Differences models.* This approach assesses county enrollment and well-child exam claims at the end of the HRL treatment period in year two (2011) relative to the county's enrollment and claims in the year prior to treatment (2009), as a baseline or pre-

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[7] We attempted to estimate RD models that included both of the HRL treatment cutoff points (years one and two) to examine differences in enrollment between the two treated groups. However, due to high collinearity between the terms representing the first and second cutoff points, we could not test for these differences. Therefore, we only tested for differences at the second cutoff point for each RD and VAM-RD model to capture the sample's complete exposure to the HRL intervention. One can consider the treatment effect at the second cutoff to be the same as the treatment effect at the first cutoff because of their statistical similarity.

[8] Note that not all county covariates are time-varying due to census data collection limitations, and the same value is used for 2009-2011.

treatment measure. The DID specification adds indicators for the treatment years and an interaction between the last treatment year, designated 'Post', and the HRL treatment variables, shown in (4).

(3) $Y_{ijk} = \alpha + \beta_T T + Q_i + Z_{ij} + \beta\, 2010 + \beta_{Post} 2011 + \delta_{Post*Treat} 2011 * T$

Where $\delta_{Post*Treat}$ is the estimate of the treatment effect, Q_i is the county's QAV included as a control variable, and the 2010 and 2011 year indicators capture exogenous shocks related either to the kindergarten cohort or other policy changes during the year. The primary assumption for DID is that treatment is exogenous. Therefore, these estimates are conditioned on the assumption that using the QAV to determine treatment status renders the HRL treatment as exogenous. Because this approach uses a limited portion of the variation by examining only within-county variation to identify the HRL treatment effect (i.e., switching from no treatment to HRL treatment in 2009-2011), estimates may be less precise. This method also assumes that statewide pretreatment trends are the same for all counties.

3. *Value-added RD models.* A value-added model (VAM) relates a current outcome to the prior year's outcome by including the prior year outcome value as an independent variable, known as a lagged dependent variable (DV). This approach can capture gains or changes in enrollment and well-child exam claims from the baseline year in 2009 because including the lagged outcome value as a covariate pulls this variation out of the outcome variable on the left-hand side, and therefore reduces the measure to its change from the prior year. These models will be extensions of (1) and (2) with the lagged outcome measure, shown in (4) and (5), and are referred to as the VAM-RDs.

(4) $Y_{ijk} = \alpha + \beta_{Y_{j-1}} Y_{ij-1k} + \beta_T T + \beta_Q (Q_i - Q) + \beta_{Q^2} (Q_i - Q)^2 + Z_{ij} + \beta\, 2011$

$$(5)\quad Y_{ijk} = \alpha + \beta_{Y_{j-1}} Y_{ij-1k} + \beta_T T + \beta_Q (Q_i - Q) + \beta_{Q^2} (Q_i - Q)^2 + \beta_{TQ} T (Q_i - Q) + Z_{ij} + \beta\, 2011$$

Where Y_{ij-1k} represents the outcome measure (k) for a county (i) in the j-1 year.

One of the key assumptions of VAMs is that the model is fully specified. The problem with using lagged dependent variables here is that a county's lagged outcome value is also likely related to other unobserved county characteristics that are not controlled for in the model specification. This creates a relationship between a covariate and the error term and biasing not only the lagged DV estimate, but also the other county covariates included in the model estimates (Bond, 2002). In this case, the DID estimates may be preferred. If the bias from the lagged DV is negligible, then the lagged DV will add power to the analyses because it is a strong predictor of future DV values and may mitigate the loss in precision in the DID estimates. Here, both the VAM-RD and DID results are not the primary impact estimates, but are used to test for robustness of the RD estimators.

Focus group and interview design

The focus group and interview participants were school nurses and school administrators. Participants were asked to read and sign a consent form to participate in the research study prior to the start of the session. There were no participants who declined to participate. We developed a schedule of questions for the focus groups based on the goals of the qualitative research. These were: assess best practices in school-based and community outreach efforts, document the specific activities involved in the implementation of the HRL intervention, assess the extent to which the HRL intervention activities accomplished the stated goals and objectives of the intervention based on the intervention logic model, and identify any other hidden treatments.

The focus groups were conversational but followed a specific set of questions to allow for the free flow of information and description of the participant's experience using an open response format (Strauss & Corbin, 1998). The focus group discussion was moderated in order to reach a group viewpoint as much as possible, using prompts when appropriate to keep the conversation on point and to get everyone involved in the discussion. Questions were typically asked in the same order, though sometimes a digression was appropriate in order to probe beyond the stated answers to the prepared questions (Berg, 2004). The protocol was as follows:

1. Do you think the current outreach/enrollment methods have been effective? Why or why not?
2. How do you think the current outreach/enrollment methods could be improved?
3. Has communication among school nurses, parents, SHACs and other partners been effective? Why or why not?
4. Did you face any challenges to getting parents to enroll their children in Health Choice/Health Check? If so, what were these challenges?
5. Did certain enrollment methods work better with different types of families? If so, please explain.
6. Has the intervention helped in better targeting underserved minority groups for outreach/enrollment? If so, how and to what extent?
7. From this intervention, what have you found to be the best practices for outreach/enrollment?

Focus group researchers included a project investigator who asked the questions from the focus group protocol and moderated the discussion, and a project research assistant who recorded participant answers. We analyzed these data by extracting the substantive categories from the participants responses and then placing the categories into broader themes composing the larger central phenomena under study, such as successful outreach strategies (Berg, 2004; Strauss & Corbin, 1998).

Results

Descriptive Analysis

Kindergarten Health Assessment

HRL KHA sample. Table 1.2 shows sample proportions for a selected set of health characteristics (all health characteristics and KHA indicators shown in Figure 1.2). Note that the variable values in Table 1.1 represent all counties in NC, and the sample in Table 1.2 is a subset of the pilot HRL counties (12 of 16), and therefore represent the NC counties with the highest economic need (as measured by the QAV). Items 1 and 2 in Table 1.2 are the key parent report items from the KHA. Item 1 is the central identification strategy of the HRL intervention—child health insurance status. Approximately nine percent of parents did not provide an answer for this item, and of those that did, about four percent of kindergarten children appear to have no health insurance coverage. A majority of the KHA sample (51.1%) reported enrollment in Medicaid, and most of the sample reported a regular place for medical care other than a hospital; however, the missingness on this variable is considerable (20.6%). In terms of health and developmental concerns, almost two-thirds of the sample (64.2%) reported some pertinent illness, risk, or developmental problem

Missingness comparison between HRL and statewide KHA sample. Table 1.4 compares[9] the rates of missingness for the parent report items on the KHA form between the HRL KHA sample and the statewide probability sample data collected in 2008 to detect whether the HRL efforts improved item completion. Looking at the column *Difference*, it is clear that there were lower rates of missingness in the HRL sample for each of the parent report items listed here. This difference was over 15 percentage points for three of the items, including the child heath insurance coverage item, which was central to the efforts of the HRL initiative. While overall missingness on these items is still considerable, they are much lower in the 2010 HRL KHA sample.

Enrollment and well-child exam rates

Table 1.3 shows the statewide enrollment and well-child rates for kindergarten-aged children by year and HRL status. As described in the data section above, we suspect that the 2011 ACS estimates of the number of children in each county who are living below 200% FPL underestimate the *true* number of children living below 200% FPL and are thereby eligible for SCHIP or Medicaid. As a result, our enrollment and well-child exam rates are significantly above 100 percent because the estimated denominator we use in our calculations is lower than the 'true' denominator. Therefore, our descriptive statistics merely provide a *relative* measure of differences in rates between the groups, and do not represent *actual* rates.

The enrollment rates on the left-hand side of the table indicate that between 2009 and 2010 there was a considerable increase in enrollment statewide—over 40 percentage points by our metric. This is likely the result of the CHIPRA expansion legislation in 2009, which would be an exogenous policy shock for all counties in the study. Enrollment continued to

[9] Note that the two KHA datasets are not equivalent because of the differences in their sampling strategies; the state sample is representative of all counties, and the HRL sample is representative of counties with high economic need.

increase in 2011, but not as drastically (~12 percentage points). Looking at enrollment by treatment status, one can see that HRL counties have a 2.2 percentage point lower enrollment rate then non-HRL counties before the start of the intervention in 2009. At the end of the HRL intervention, this gap between the two groups remains the same, in spite of growing wider in 2010.

The well-child exam rates are on the right-hand side of the table. These numbers also indicate that between 2009 and 2010 there was a substantial increase in the number of children receiving a well-child exam (~30 percentage points), though the increase is not as large in terms of percentage points as the change in enrollment. Between 2010 and 2011, the rate of well-child exams continued to increase (~ 10 percentage points) but not as drastically as the 2009-10 increase, following the pattern seen with enrollment rates. HRL counties have a slightly higher well-child exam rate in 2009 (~3 percentage points) than non-HRL counties. While this difference is eliminated in 2010, the relative difference in well-child exam rates between HRL and non-HRL counties at the end of the study (~2 percentage points) is similar to the difference observed in the pre-study year.

Regression Discontinuity

Specification tests

Graphical Analysis. We created scatterplots of several polynomial forms of the QAV and both outcome variables to check for the presence of non-linear relationships and assess the number of higher order polynomial terms. These analyses indicated that there were not curvilinearities in the relationship between the QAV and the outcome variables. Based on these results, we added a squared version of the QAV to the RD models. We present the graphs of enrollment rates in Figure 1.3 (a) and (b), and well-child exam rates are shown in Figure 1.4 (a) and (b), where 1.3 and 1.4 (a) plots the outcome against the QAV, and 1.3 and 1.4 (b) plots the outcome against the QAV squared. The graphs pool 2010 and 2011 county-level data, and the black vertical line represents the treatment cutoff for year-two of HRL. These figures also helped us to determine the appropriate bandwidth restrictions for the outcome analysis.

Falsification tests. The coefficients on the HRL variables were not significant in our falsification tests using the 2009 data. This suggests that any treatment effect we determine in the RD analysis is robust to our specification and estimation procedure (Van Der Klaauw, 2008).

Outcome analyses

The results for the enrollment analyses are displayed in Table 1.5, and results for well-child exam rates are displayed in Table 1.6. We tested for differences in the slopes between treatment groups by including an interaction between HRL and the distance from the treatment cutoff value, shown above in equations (2) and (5), but this term was not significant. Therefore, we only present RD and VAM-RD results for the models shown in equations (1) and (4) above that test for differences at the year-two treatment cutoff, which captures the sample's entire exposure to HRL. In the RD and VAM-RD models, the HRL treatment effect for kindergarten-aged children is represented by the variable HRL.

We report the RD and VAM-RD results using a bandwidth of 3 (optimal bandwidth) and for the full sample of counties. The full sample results are shown for comparison only because the effect of a treatment identified with RD generalizes exclusively to units that are clustered around the cutoff (via bandwidth restriction). While we tested several bandwidths, we present only the optimal bandwidth of three. This was determined by the distribution of units around the treatment cutoff using graphical analysis, and to balance statistical power and precision. The model results using alternate bandwidths are very similar and are available from the authors.

Enrollment rates. Table 1.5, columns 1 and 2 display the RD estimates of the effect of HRL on enrollment rates. The results in the first column are restricted to those counties within a bandwidth of 3, and the results in the second column use the entire sample of counties with no bandwidth restriction. Restricting the sample to those within 3 units of the cutoff (based on the QAV) reduces both the magnitude and power of the coefficient on HRL, moving from 0.091 to 0.046. The coefficient is very small and positive, but it is not statistically significant.

Well-child exam rates. Table 1.6, columns 1 and 2 displays the RD estimates of the effect of HRL on well-child exam rates. As in Table 1.5, the results in the first column are restricted to those counties within a bandwidth of 3, and the second column includes the entire sample of counties. Restricting the sample to those counties within 3 units of the cutoff does not change the magnitude or the power of the coefficient on HRL appreciably. As with enrollment, the coefficient is very small and positive, but is not statistically significant.

Difference-in-Differences

The enrollment rate results from the Difference-in-Differences (DID) estimation are displayed in column 3 of Table 1.5, and well-child results are displayed in column 3 of Table 1.6. This analysis allowed us to use three years of data by including the year prior to HRL treatment as a baseline comparison and therefore also increased the sample size. In these models, the HRL treatment effect is captured by the variable HRL*post, an interaction term between the indicator for treatment and the indicator for 2011.

Enrollment rates. As in the RD analysis presented in columns (1) and (2) of Tables 1.5 and 1.6, the HRL DID coefficient on enrollment rates for kindergarten-aged children was small and positive, but it was not statistically significant. However, the DID analysis confirms some of the trends in enrollment shown in the descriptive statistics. The positive and significant coefficients for 2010 and 2011 indicate that there were year-specific factors such as policy or economic changes that increased enrollment during the treatment time period for all counties in NC.

Well-child exam rates. The HRL DID treatment effect on well-child exam rates for kindergarten-aged children was smaller than the estimated effect in the RD analysis (0.012 and 0.043, respectively), but again did not reach statistical significance. As with the enrollment rate DID analysis, the positive and significant coefficients for 2010 and 2011 indicate that there were year-specific factors like policy and economic changes that increased well-child exam rates for all NC counties during the treatment time period. However, these exogenous changes did not have as strong of an effect on well-child exam rates as they did for enrollment rates; the effect in 2010 is 0.44 for enrollment rates, and 0.31 for well-child exam rates.

Value-added Regression Discontinuity Models

Enrollment rates. VAM-RD results for enrollment rates are displayed in Table 1.5 in columns 4 and 5. Column 4 restricts the sample to a bandwidth of 3, and column 4 includes the entire sample of counties. The effect of HRL is positive and significant, indicating a 12.2 percentage point increase in enrollment rates for kindergarten-aged children in the HRL intervention counties. Including the lagged dependent variable does appear to increase the power of our HRL estimate, as the t-statistics are larger in the VAM-RD than they are in the standard RD.

Well-child exam rates. VAM-RD results for well-child exam rates are displayed in Table 1.6 in columns 4 and 5. Column 4 restricts the sample to a bandwidth of 3, and column 4 includes the entire sample of counties. The VAM-RD HRL treatment effect on well-child exam rates for kindergarten-aged children is also positive and statistically significant. The coefficient indicates that HRL counties experienced an 8.6 percentage point increase in well-child exam rates for kindergarten-aged children during the study time period. As with the enrollment VAM-RD model, including the lagged dependent variable increases the power of the HRL estimate.

Summary

Overall, we cannot confidently conclude that the HRL intervention had a statistically significant effect on enrollment or well-child exam rates for kindergarten-aged children. Although the VAM-RD specification produced positive and significant effects for both enrollment and well-child exams, this statistical significance was not corroborated in the RD and DID estimation. We consider these identification strategies to be the best evidence of a causal treatment effect due to the potential bias in VAMs. Though the coefficients were positive in the RD and DID analyses, they were not statistically significant. We can conclude that there were secular changes during the treatment time period (e.g. policy expansions of CHIP eligibility) that were associated with increased enrollment and well-child exam rates for all counties.

Focus Group and Interview Data Analysis

HRL Program Effectiveness

Overall, participants felt that HRL helped to reignite school efforts to inform parents about public health insurance and to ensure that the KHA forms are filled out properly. It also helped to compensate for reductions in state agency funding for outreach positions that linked schools and public health insurance (i.e., Health Check coordinators). However, the participants did not feel that there were many kindergarten children to identify without insurance. They felt that there was a greater need for outreach to children in older grades where there are higher rates of uninsured. One possible explanation is that parents may have already signed up for public insurance to get the KHA form filled out for kindergarten registration because a physical is expensive without coverage. In grades where there are no required health documents or immunizations, parents are less likely to keep up with their children's health insurance coverage.

Best Practices for Outreach

Parents and school staff respect school nurses and see them as a trusted source of health information, and all agreed that the school nurse is a key part of school-based health outreach. Still, the participants stressed that "everyone who sees the [KHA] form needs to interact with parent." This means that all school personnel and health care providers who are face-to-face with parent should encourage enrollment because face-to-face discussion was the most effective outreach strategy based on the experiences of the participants. For schools, this involves training all personnel including principals, administrative staff, teachers, and the faculty who work with English Language Learners, and giving them key information about the program (e.g. income eligibility guidelines). This helps the staff feel prepared to answer questions, and are therefore more comfortable talking with families about the program. When this information is communicated through the school nurse, people listen.

Another important point is constructing clear and simple messages. Outreach materials should be uncomplicated so that the information about health insurance can be clearly and quickly understood. This can help to reduce any stigma of seeking information if parents have to spend a lot of time looking at a Medicaid poster for small detailed information. Participants suggested that outreach technology could be updated to communicate more directly with parents such as texting reminders to reenroll their child. Program staff also used the HRL website to provide a central location for resources such as forms, contacts, and brochures for the convenience of school staff and parents.

Other ideas for identifying eligible and un-enrolled children are: examining insurance status at vision screenings that occur in grades one, three, and five, routine insurance checks by the nurse when a student presents with illness, collecting insurance information on a school's required emergency contact card, and attaching an insurance application to the KHA form or other documents required from parents. Another way to measure program success or as a process evaluation metric would be to analyze the Department of Social Services data on appointments made for families to complete the paperwork for enrollment in health insurance. Tracking their data would show the number of applications they received and the number parents who show up for their appointments, since school staff never find out if families followed-through with the process.

There were also some considerations for special populations. Families who are homeless or in transition are afraid to turn in forms because they fear they will be seen as an unfit parent and 'have their children taken away" by social services. Additionally, participants from counties with a high percentage of transient populations said these families are generally not aware that their coverage follows them throughout the state. Creating a website that children and adolescents can navigate when their parents do not have access technology, do not understand the program, or do not speak English may also help to reach these families.

Best Practices for Program Implementation

Overall, for a successful implementation outreach coordinators should tailor their efforts in order to “meet people where they’re at”. This means helping parents, teachers, principals and other local professionals to overcome any challenges in order to make it as easy as possible for them to get to the next step in the outreach or enrollment process and includes activities such as pre-addressing envelopes for enrollment paperwork, describing the documentation parent’s will need to show eligibility for the program. To ensure the completeness of the KHA form, school staff can work with parents to fill out their section of the form during kindergarten registration.

Program staff also highlighted the importance of the partnerships HRL made with the public school system; particularly the agreement from superintendents that helped to get cooperation and compliance from the lead contacts in each county to “get on board with the initiative.” Talking with these contacts in person and going over the contract, program expectations, and intervention goals was a critical piece of compliance with implementation as well. Relatedly, project staff must have respect for the local authority and norms of operation. Outreach staff should be aware of a school’s protocol and develop an understanding of “how they do things” before trying to modify or change processes to implement the program. This includes modifying practices for both large and small school systems. The development of networks and partnerships with other nonprofits and public programs like Head Start helped to increase the scope of the project and to understand the norms of the local area. This can help to 'institutionalize' the goals of the HRL program by having a standing item included on partnering agencies' regular meeting agendas.

In the same way that outreach messages need to be simple and direct, the tasks for lead contacts and school staff should also be clear. Program startup was challenging because school staff expressed confusion about the actual tasks they needed to complete. In order to improve communication the HRL staff developed action steps for school contacts, giving people clear directions by breaking down tasks into simple steps. HRL coordinators stressed that repeating these messages including identifying the required tasks and objectives, helped provide direction and gave clear simple guidelines about what was expected of local coordinators.

Discussion

Uninsured children are a challenge for policymakers and practitioners because they are much less likely to receive routine preventive care, which is detrimental to child well-being in the short- and long-terms and impose significant individual and societal costs. But in order to reap the benefits of preventive care using health insurance as a policy lever, it is important to know whether providing health insurance will influence the way that parents access care for their children. In this paper, we present a comprehensive evaluation of a CHIPRA Cycle I Outreach and Enrollment grant in North Carolina for the initiative *Healthy and Ready to Learn* (HRL) that was designed to help identify and enroll uninsured kindergarten-aged children in areas of high economic need. We used a strong research design with multiple years of data to estimate the causal effect of the HRL initiative on Medicaid and SCHIP enrollment rates and well-child exam rates for kindergarten-aged children. We were also able to capture some of the best practices for school-based health insurance outreach using qualitative methods.

Although the HRL effects for both enrollment and well-child claims were positive in the RD analysis, they were not statistically significant. RD is the strongest nonexperimental design for estimating unbiased treatment effects, but it requires a larger sample size to detect effects. Because this method had less statistical power, we also conducted a Difference-in-Differences analysis to enhance power by adding data from the baseline year and estimated a 'before and after' treatment effect. Consistent with the RD results, the effect of HRL was positive but was not significant. We also checked our results using a VAM-RD model. While the VAM-RD increased the power and precision of our HRL estimate allowing it to reach significance, these results were not consistent with our prior findings from the presumably less biased RD and DID estimates. Overall, our quantitative analyses suggest that the differences in Medicaid and SCHIP enrollment rates and well-child exam rates between counties that received the HRL treatment from those who did not receive treatment were not robustly statistically significant. It could be that the immediate effects were too small to be statistically significant with the RD. This is in accordance with the qualitative evidence that school staff did not feel there were many kindergarten-aged children who were uninsured. We did find more broadly that there was an increase in both enrollment and well-child exam rates for all counties during the study time period.

There are several possible explanations for why the HRL results did not achieve significance. First, the enrollment data showed a drastic 50 percent increase in enrollment and well-child exam claims during the first year of treatment. This is probably the result of two things: (1) Federal CHIPRA legislation expanding program eligibility and funding, and

(2) an increased number of income-eligible and uninsured children stemming from job loss during the economic recession. In the context of these large economic and policy changes, the unique effects of HRL may have been lost in the noise created by the other changes or were too small to detect given the power of the sample. There may have been too few HRL pilot counties to detect the effects of the full two-year 'dosage' of HRL. Furthermore, the quantitative assignment variable used in HRL only met the minimum requirement for a valid RD, with four unique values above and below the cutoff (Schochet, et al., 2010). This minimal variation in the QAV may not have been adequate to detect a causal effect. Perhaps having more counties who were under treatment for a longer period of time would have enhanced the power to find an effect.

It is also possible that the counties with a lower need-index score (mostly non-HRL counties) had a greater potential for Medicaid and SCHIP enrollment growth. The families in these counties were wealthier on average (based on the need index ranking), and therefore the observed changes in SCHIP policy and the economy may have made a larger difference in expanding enrollment for these families. Whereas in higher need counties—where HRL was implemented—the changing economy and policy were less likely to change a family's eligibility status from the status quo, leaving less room for enrollment to grow. Alternatively, focus group participants noticed that prior to kindergarten entry, some parents might have already signed up for public insurance to get the KHA form completed *for* kindergarten registration to avoid the expense of getting a physical without health insurance coverage. This is certainly possible given that the HRL initiative took place in the counties ranking highest in economic need.

On the other hand, there is some research indicating that there is a lower disparity in citizens access to health care in rural areas than in urban areas (Ziller, et al., 2012). This is because rural communities tend to have more informal safety nets whereby there are fewer barriers for the uninsured to find necessary care, such as doctors offering services pro-bono or at a discount for families who they know are struggling (Taylor et al., 2003). Many of the HRL counties are rural, therefore the group under treatment may not have had difficulties accessing healthcare regardless of insurance status. Moreover, some rural health clinics receive special compensation through Medicare and Medicaid to provide care in underserved rural communities (Hartley, Gale, Leighton, & Bratesman, 2010). A recent survey found that 86% of these clinics offer free or discounted care to patients who are uninsured or do not have adequate health care coverage (Hartley, et al., 2010). If HRL counties have these types of safety net mechanisms, this could dampen the potential impact of HRL in rural communities. Therefore, it is possible that the expansion of CHIPRA made a greater difference for families in counties with large urban areas who may not have these safety nets (e.g. Charlotte-Mecklenburg, Wake (Raleigh)) that were not included in the HRL intervention.

Increasing the completion rate of the parent report items on the top of the KHA form was a sub-goal of the HRL initiative since school staff were instructed to examine the health insurance item in this section to identify uninsured children. For this reason, we compared the rates of missingness for the parent report items between the HRL KHA sample from 2010 and the statewide KHA sample from 2008 to detect whether the HRL efforts were influential on completion rates. We found that there were lower rates of missingness in the HRL sample for each of the parent report items, with more than a 15 percentage point difference on three items including child heath insurance coverage. This trend corroborates some of the qualitative data suggesting that the HRL initiative "re-energized elementary schools to get the KHA form completed" and that school staff were helping parents to fill out the entire form at kindergarten registration events. While this is not causal evidence, the consistent pattern of reduced missingness across items in the HRL sample may suggest that HRL had an influence on increasing the completion rate for the parent items on the KHA form. However, since we documented significant changes in both the enrollment and well-child exam rates during this time period (2008-2010), these same secular or policy changes (i.e. CHIP expansion) may have also influenced KHA completion.

We also presented results from focus groups and key informant interviews with school nurses and project staff in the 16 pilot counties. These findings suggest that HRL was successful at raising awareness about public health insurance and highlighting the importance of having parents and physicians fill out the KHA form properly. Other important findings include: using clear and concise outreach messages and steps for local action, training school personnel and medical care providers on SCHIP and Medicaid to enable them to communicate with parents face-to-face about the program, integrating health insurance screenings into other school documents and routines, expanding outreach to older children, and being able to adapt to individual needs and "meet people where they're at" to make enrollment possible. These findings may be helpful for the successful implementation of other school-based and community outreach efforts to enroll children in public health insurance and to increase awareness of the importance of preventive care.

While we would not conclude that HRL had no effect, we can say that if the small effects we detected were significant, the effect sizes are large enough that future research should further test the program to see if it can be replicated in other areas, especially if the sample size can be larger. It may be that programs like HRL should continue and be implemented on larger scale but with another rigorous evaluation where there is sufficient power. Another policy alternative is working toward the more streamlined Express Lane Eligibility approach where children are identified and enrolled through an information-sharing network of need-based public programs such as the National School Lunch Program or the Supplementary Nutrition Assistance Program. These approaches can increase coverage, save money, and make enrollment procedures much more modern and efficient. However, NC must overcome the differences between programs in determining eligibility and enable electronic information-sharing among programs before such an approach is feasible. The Affordable Care Act (ACA) will undoubtedly play a major role in insuring low-income and working-poor children and enabling access to care in the coming decade which will be of primary importance in children's public health policy research (Morrissey, 2012).

Another exciting avenue for future research is linking the KHA data to children's academic outcomes. During KHA data collection, schools affixed a label on the form that includes the child's WISE-ID, a unique identifier assigned by the Department of Public Instruction (DPI). This will allow us to analyze the academic outcomes of children in pilot counties at the first public school assessment in third grade using administrative data from DPI when the children are tested for the first time in third grade, and in each grade thereafter. Even though we did not detect an HRL treatment effect, the information gleaned during the data collection process may allow us to more closely examine the link between child health factors upon school entry and later academic outcomes.

TABLE 1.1: COUNTY-LEVEL VARIABLES, DESCRIPTIVE STATISTICS AND DATA SOURCES FOR 2010

Variables	Mean and SD	Data Source
Controls		
Population growth rate	12.3 (11.5)	Office of State Management and Budget
Number of children ages 0-5	6350.5 (10397.6)	U.S. Census
Unemployment rate	11.4 (2.3)	Bureau of Labor Statistics
School Nurse to student ratio	1029.2 (445.2)	NC School Nurse Council
Number of physicians per 10,000	7.2 (4.6)	NC Division of Health Service Regulation
Number of inpatient facilities	257.8 (400.4)	NC Division of Health Service Regulation
Outcome variable components		
Numerator		
Total number of five year-old children enrolled in Medicaid and SCHIP	647.3 (858.8)	NC Division of Medical Assistance
Total number of five year-old children who received a well-child exam	522.6 (687.4)	NC Division of Medical Assistance
Denominator		
Population age 5 years	1264.4 (2076.6)	U.S. Census
Survival rates by age (Life Tables)	99.9	NC State Center for Health Statistics
Percent of children ages 0-18 at or below 200% of the FPL	50.5 (9.6)	U.S. Census, American Community Survey

TABLE 1.2: SAMPLE PROPORTIONS FOR SELECTED HEALTH CHARACTERISTICS FROM THE KINDERGARTEN HEALTH ASSESSMENT (KHA) FORM

Parent Report		
1. Child health insurance coverage		
	Medicaid	51.1
	Private Insurance/HMO	28.1
	Other	8.0
	None	3.8
	Missing	8.9
2. Place where your child gets regular health care		
	Health Department	5.7
	Hospital	4.9
	Community Health Center	3.1
	Private care clinic	53.1
	Other provider	11.6
	No regular care	1.0
	Missing	20.6
Provider Report		
3. Body Mass Index status		
	Underweight	1.6
	Normal	73.0
	At-risk for overweight	6.1
	Overweight	7.6
	Missing	11.8
4. Child has a pertinent illness, risk or developmental problems		
	Any	64.2
	Allergy	6.6
	Asthma	8.5
	Attention or learning disorder	1.8
	Diabetes	0.1
	Emotional or behavioral	1.6
	Obesity	1.0
	Speech or language	4.3
	Vision	1.2
5. Developmental Domain concern identified		
	Emotional/Social	2.4
	Problem solving	2.1
	Language/Communication	4.1
	Fine motor skills	3.1
	Gross motor skills	0.9
6. Child passed hearing test		
		82.6
7.Child passed vision test		
		78.0
Observations		*15,397*

TABLE 1.3: ENROLLMENT RATES AND WELL-CHILD EXAM RATES BY YEAR AND BY TREATMENT STATUS

	Medicaid/SCHIP enrollment rate for kindergarten-aged children			**Well-child exam rate for kindergarten-aged children**		
Year	*All Counties*	*HRL Counties*	*Non-HRL Counties*	*All Counties*	*HRL Counties*	*Non-HRL Counties*
2009	80.4	79.2	81.4	65.4	66.9	64.1
2010	122.7	114.8	124.1	96.0	96.1	96.0
2011	134.6	133.4	135.6	105.6	106.6	104.7

TABLE 1.4: KINDERGARTEN HEALTH ASSESSMENT (KHA) SAMPLE AND STATEWIDE KHA SAMPLE OF THE PERCENT MISSING ON KHA PARENT REPORT ITEMS

	Percent missing		
Item Name	State sample (2008)	HRL sample (2010)	Difference
Child health insurance coverage	24.4	8.9	-15.5
Place where your child gets regular health care	25.2	20.6	-4.6
Child birthdate	18	9.48	-8.52
County of residence	24.4	8.57	-15.83
Zip code	21.8	3.05	-18.75
Race	24.7	18.9	-5.8
Hispanic or Latino origin	44.8	35.9	-8.9
Observations	*4068*	*15,397*	

TABLE 1.5: MODEL RESULTS FOR THE EFFECT OF HRL ON MEDICAID AND SCHIP ENROLLMENT RATES FOR KINDERGARTEN-AGED CHILDREN

	(1)	(2)	(3)	(4)	(5)
	RD cutoff 2: Bandwidth of 3	**RD cutoff 2: Full sample**	**Differences in Differences (2009-2011)**	**VAM-RD cutoff 2: Bandwidth of 3**	**VAM-RD cutoff 2: Full sample**
HRL county in current year (HRL=1)	0.046	0.092		0.12*	0.16*
	(0.84)	(1.70)		(3.89)	(3.87)
HRL*post			0.047		
			(1.29)		
Distance from year-two cutoff	0.19	-0.055		0.20	-0.026
	(0.80)	(-0.95)		(1.64)	(-1.35)
Distance from year-two cutoff squared	-0.0065	0.0011		-0.0068	0.000071
	(-0.85)	(0.62)		(-1.79)	(0.12)
County School Nurse-Student ratio	-0.000039	-0.000066	-0.000058	0.0000085	-0.000024
	(-0.86)	(-1.28)	(-1.26)	(0.31)	(-0.89)
County growth rate	-0.0027	0.0018	0.00081	-0.0029*	-0.00067
	(-1.06)	(0.40)	(0.22)	(-2.23)	(-0.27)
Number of Primary Care Physicians in county - per 10K	-0.0048	0.0013	-0.0025	0.0053	0.0060
	(-0.97)	(0.21)	(-0.41)	(1.47)	(1.78)
County unemployment rate	-0.011	0.0080	-0.0056	-0.010	-0.0017
	(-0.57)	(0.47)	(-0.38)	(-1.30)	(-0.22)
Total number of children ages 0-5 in county	-0.0000068	-0.0000055	-0.0000064	0.00000051	0.00000080
	(-1.55)	(-1.27)	(-1.45)	(0.28)	(0.42)
Number of hospital beds in county	-0.000047	-0.000045	-0.000033	-0.00016	-0.00011
	(-0.34)	(-0.32)	(-0.25)	(-1.86)	(-1.37)
Number of hospitals in county	0.078*	0.067	0.060*	0.049*	0.037
	(2.21)	(1.93)	(2.08)	(2.52)	(1.85)
2011	0.099	0.11*	0.55*		
	(1.69)	(2.29)	(9.03)		
HRL county in year one or two			-0.051		
			(-1.02)		
2010			0.46*		
			(6.12)		
Lagged enrollment rate				1.18*	1.14*
				(10.62)	(9.39)
Constant	1.40*	1.08*	0.91*	0.36*	0.28*
	(4.30)	(3.93)	(5.76)	(2.34)	(2.05)
Observations	124	200	300	124	200

t statistics in parentheses
* $p<0.05$

TABLE 1.6: MODEL RESULTS FOR THE EFFECT OF HRL ON MEDICAID AND SCHIP WELL-CHILD EXAM RATES FOR KINDERGARTEN-AGED CHILDREN

	(1) **RD cutoff 2: Bandwidth of 3**	(2) **RD cutoff 2: Full sample**	(3) **Differences in Differences (2009-2011)**	(4) **VAM-RD cutoff 2: Bandwidth of 3**	(5) **VAM-RD cutoff 2: Full sample**
HRL county in current year	0.043	0.044		0.086*	0.079*
(HRL=1)	(0.94)	(1.07)		(3.14)	(3.01)
HRL*post			0.012		
			(0.52)		
Distance from year-two cutoff	0.23	0.023		0.14	0.0015
	(1.12)	(0.79)		(1.23)	(0.11)
Distance from year-two cutoff squared	-0.0076	-0.00088		-0.0049	-0.00050'
	(-1.17)	(-0.98)		(-1.38)	(-1.10)
County School Nurse-Student ratio	-0.000021	-0.000024	-0.000023	0.0000056	0.00000061
	(-0.54)	(-0.58)	(-0.63)	(0.22)	(0.03)
County growth rate	-0.0021	-0.0020'	-0.0021	-0.0021*	-0.0025*
	(-1.03)	(-1.40)	(-1.44)	(-2.06)	(-2.90)
Number of Primary Care	-0.0037	0.0019	0.00039	0.0056	0.0060*
Physicians in county - per 10K	(-0.89)	(0.43)	(0.10)	(1.58)	(2.14)
County unemployment rate	-0.0061	0.00091	-0.00031	-0.0027	-0.00036
	(-0.40)	(0.07)	(-0.03)	(-0.39)	(-0.06)
Total number of children ages	-0.0000062	-0.0000042	-0.0000032	-0.00000075	4.14e-08
0-5 in county	(-1.69)	(-1.25)	(-1.06)	(-0.45)	(0.03)
Number of hospital beds in	-0.000013	-0.000065	-0.000060	-0.000078	-0.000066
county	(-0.11)	(-0.67)	(-0.66)	(-0.97)	(-1.08)
Number of hospitals in county	0.053	0.049*	0.042	0.032	0.023
	(1.83)	(1.99)	(1.97)	(1.74)	(1.52)
2011	0.066	0.059*	0.37*		
	(1.48)	(2.23)	(9.04)		
HRL county in year one or two			0.013		
			(0.32)		
2010			0.31*		
			(5.59)		
Lagged well-child exam rate				1.04*	1.06*
				(9.17)	(11.29)
Constant	1.10*	0.97*	0.68*	0.29*	0.24*
	(4.12)	(4.79)	(5.49)	(2.18)	(2.55)
Observations	124	200	300	124	200

t statistics in parentheses
* p<0.05

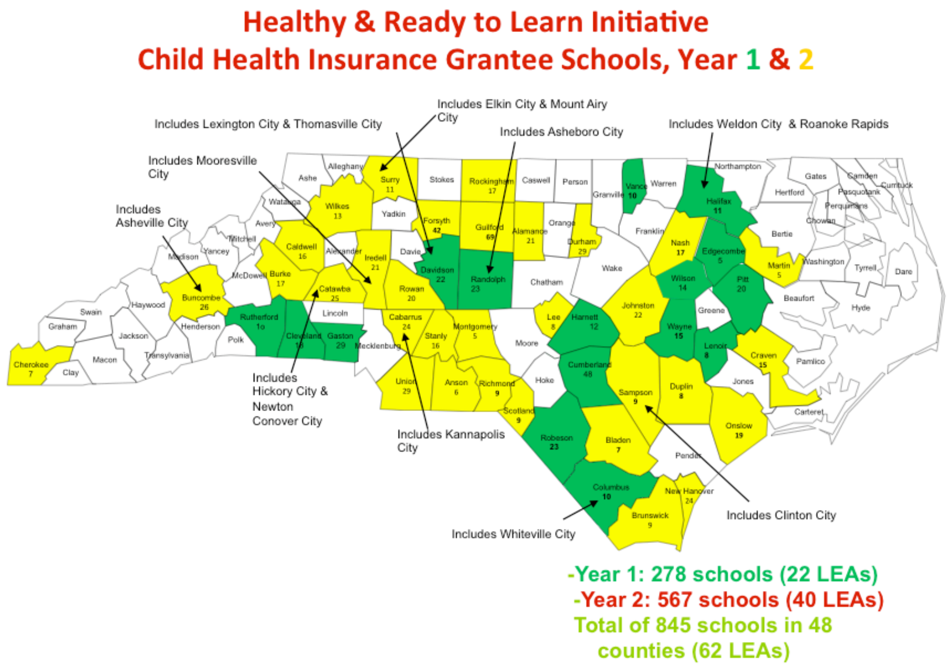
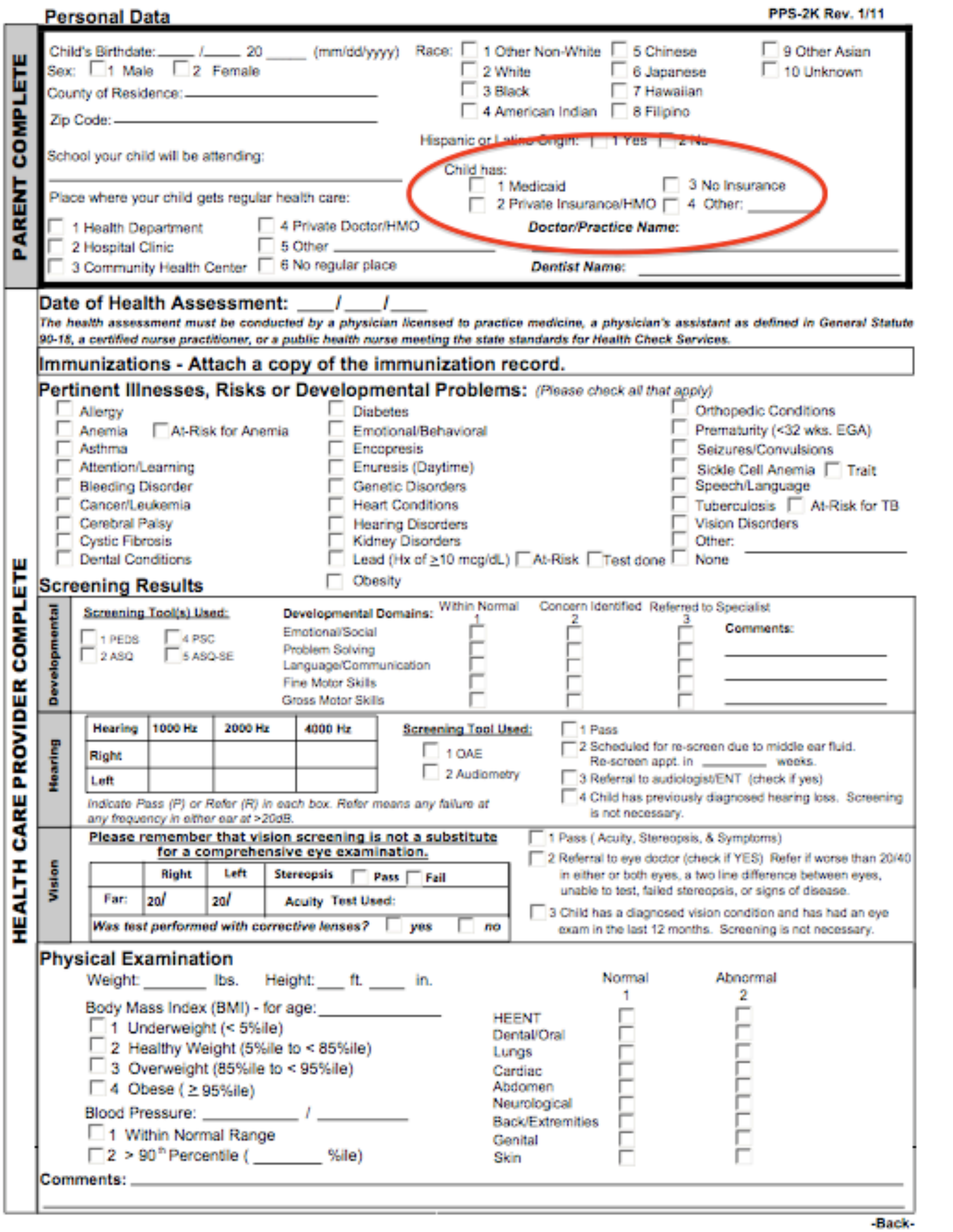


FIGURE 1.1: MAP OF N.C. COUNTIES IN THE HEALTH AND READY TO LEARN INITIATIVE TREATMENT



PARENT COMPLETE

Personal Data PPS-2K Rev. 1/11

Child's Birthdate: ____ /____ 20 ____ (mm/dd/yyyy)

Sex: ☐ 1 Male ☐ 2 Female

County of Residence: ____________

Zip Code: ____________

School your child will be attending: ____________

Place where your child gets regular health care:

☐ 1 Health Department ☐ 4 Private Doctor/HMO
☐ 2 Hospital Clinic ☐ 5 Other ____________
☐ 3 Community Health Center ☐ 6 No regular place

Race: ☐ 1 Other Non-White ☐ 2 White ☐ 3 Black ☐ 4 American Indian ☐ 5 Chinese ☐ 6 Japanese ☐ 7 Hawaiian ☐ 8 Filipino ☐ 9 Other Asian ☐ 10 Unknown

Hispanic or Latino Origin: ☐ 1 Yes ☐ 2 No

Child has:
☐ 1 Medicaid ☐ 3 No Insurance
☐ 2 Private Insurance/HMO ☐ 4 Other: ______

Doctor/Practice Name: ____________

Dentist Name: ____________

HEALTH CARE PROVIDER COMPLETE

Date of Health Assessment: ____/____/____

The health assessment must be conducted by a physician licensed to practice medicine, a physician's assistant as defined in General Statute 90-18, a certified nurse practitioner, or a public health nurse meeting the state standards for Health Check Services.

Immunizations - Attach a copy of the immunization record.

Pertinent Illnesses, Risks or Developmental Problems: *(Please check all that apply)*

☐ Allergy
☐ Anemia ☐ At-Risk for Anemia
☐ Asthma
☐ Attention/Learning
☐ Bleeding Disorder
☐ Cancer/Leukemia
☐ Cerebral Palsy
☐ Cystic Fibrosis
☐ Dental Conditions
☐ Diabetes
☐ Emotional/Behavioral
☐ Encopresis
☐ Enuresis (Daytime)
☐ Genetic Disorders
☐ Heart Conditions
☐ Hearing Disorders
☐ Kidney Disorders
☐ Lead (Hx of ≥10 mcg/dL) ☐ At-Risk ☐ Test done
☐ Obesity
☐ Orthopedic Conditions
☐ Prematurity (<32 wks. EGA)
☐ Seizures/Convulsions
☐ Sickle Cell Anemia ☐ Trait
☐ Speech/Language
☐ Tuberculosis ☐ At-Risk for TB
☐ Vision Disorders
☐ Other: ____________
☐ None

Screening Results

Developmental

Screening Tool(s) Used: ☐ 1 PEDS ☐ 2 ASQ ☐ 4 PSC ☐ 5 ASQ-SE

Developmental Domains:	Within Normal 1	Concern Identified 2	Referred to Specialist 3
Emotional/Social	☐	☐	☐
Problem Solving	☐	☐	☐
Language/Communication	☐	☐	☐
Fine Motor Skills	☐	☐	☐
Gross Motor Skills	☐	☐	☐

Comments: ____________

Hearing

Hearing	1000 Hz	2000 Hz	4000 Hz
Right			
Left			

Indicate Pass (P) or Refer (R) in each box. Refer means any failure at any frequency in either ear at >20dB.

Screening Tool Used: ☐ 1 OAE ☐ 2 Audiometry

☐ 1 Pass
☐ 2 Scheduled for re-screen due to middle ear fluid. Re-screen appt. in ______ weeks.
☐ 3 Referral to audiologist/ENT (check if yes)
☐ 4 Child has previously diagnosed hearing loss. Screening is not necessary.

Vision

Please remember that vision screening is not a substitute for a comprehensive eye examination.

	Right	Left	Stereopsis ☐ Pass ☐ Fail
Far:	20/	20/	Acuity Test Used:

Was test performed with corrective lenses? ☐ yes ☐ no

☐ 1 Pass (Acuity, Stereopsis, & Symptoms)
☐ 2 Referral to eye doctor (check if YES) Refer if worse than 20/40 in either or both eyes, a two line difference between eyes, unable to test, failed stereopsis, or signs of disease.
☐ 3 Child has a diagnosed vision condition and has had an eye exam in the last 12 months. Screening is not necessary.

Physical Examination

Weight: ______ lbs. Height: ___ ft. ____ in.

Body Mass Index (BMI) - for age: ____________
☐ 1 Underweight (< 5%ile)
☐ 2 Healthy Weight (5%ile to < 85%ile)
☐ 3 Overweight (85%ile to < 95%ile)
☐ 4 Obese (≥ 95%ile)

Blood Pressure: ________ / ________
☐ 1 Within Normal Range
☐ 2 > 90th Percentile (______ %ile)

	Normal 1	Abnormal 2
HEENT	☐	☐
Dental/Oral	☐	☐
Lungs	☐	☐
Cardiac	☐	☐
Abdomen	☐	☐
Neurological	☐	☐
Back/Extremities	☐	☐
Genital	☐	☐
Skin	☐	☐

Comments: ____________

-Back-

FIGURE 1.2: KINDERGARTEN HEALTH ASSESSMENT (KHA) FORM WITH HEALTH INSURANCE ITEM IDENTIFIED

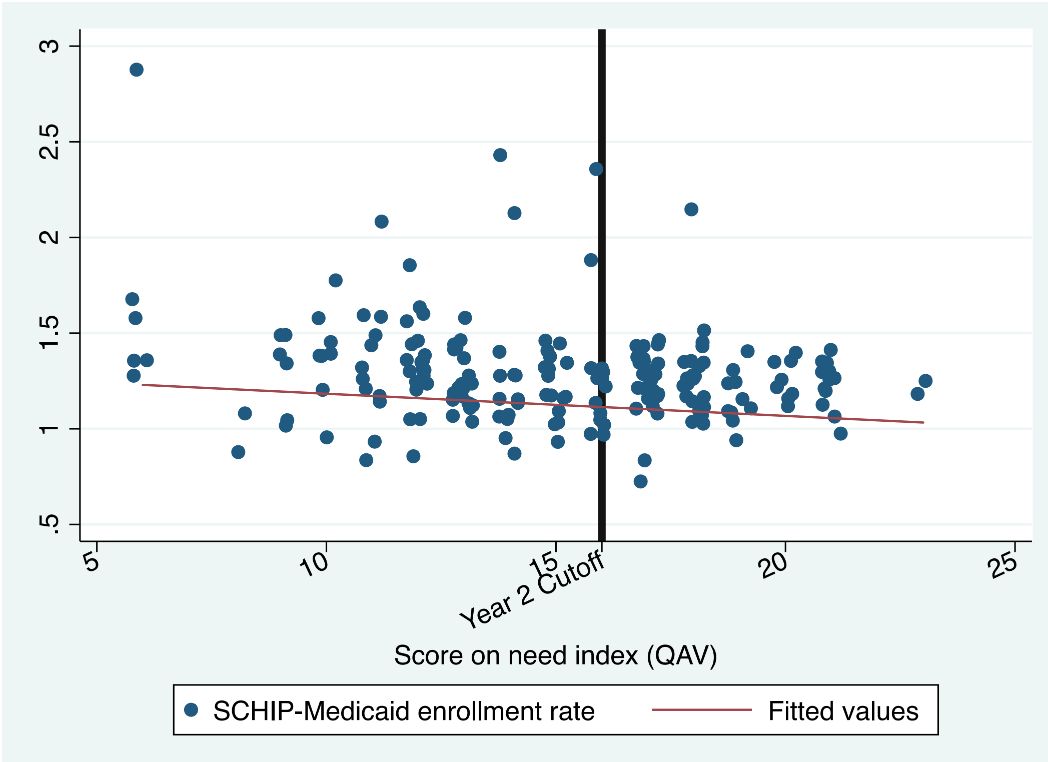


FIGURE 1.3 (A): GRAPHICAL ANALYSIS OF THE QUANTITATIVE ASSIGNMENT VARIABLE (QAV) ON COUNTY-LEVEL ENROLLMENT RATES

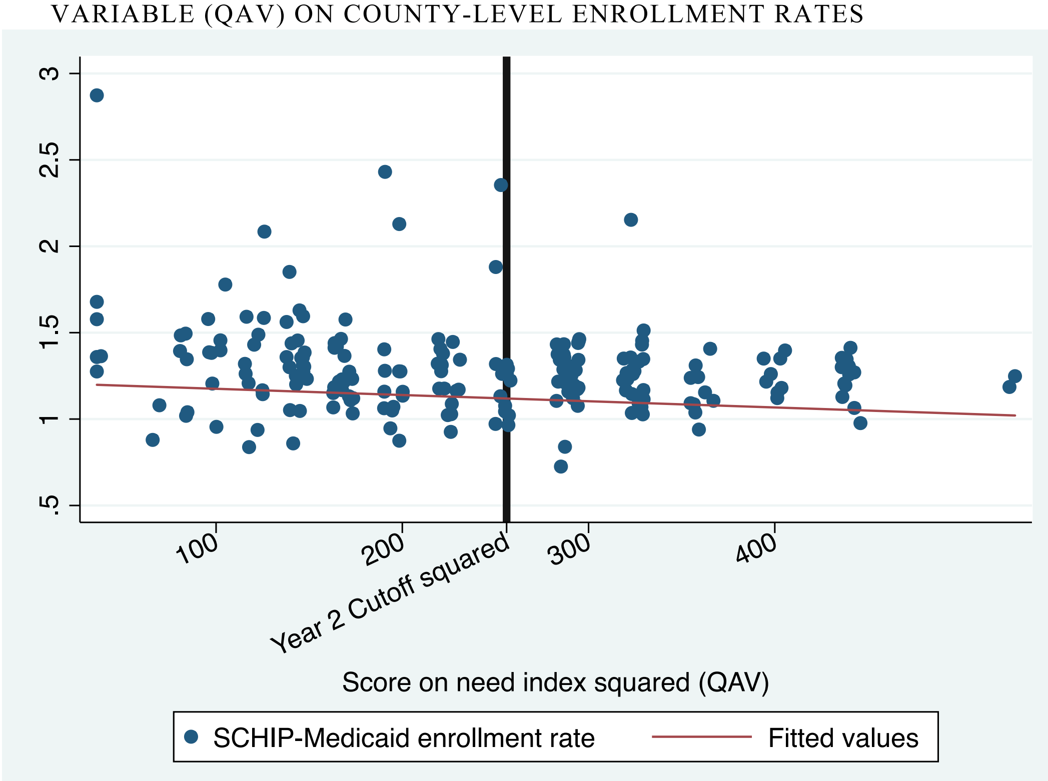


FIGURE 1.3 (B): GRAPHICAL ANALYSIS OF THE QUANTITATIVE ASSIGNMENT VARIABLE (QAV) SQUARED ON COUNTY-LEVEL ENROLLMENT RATES

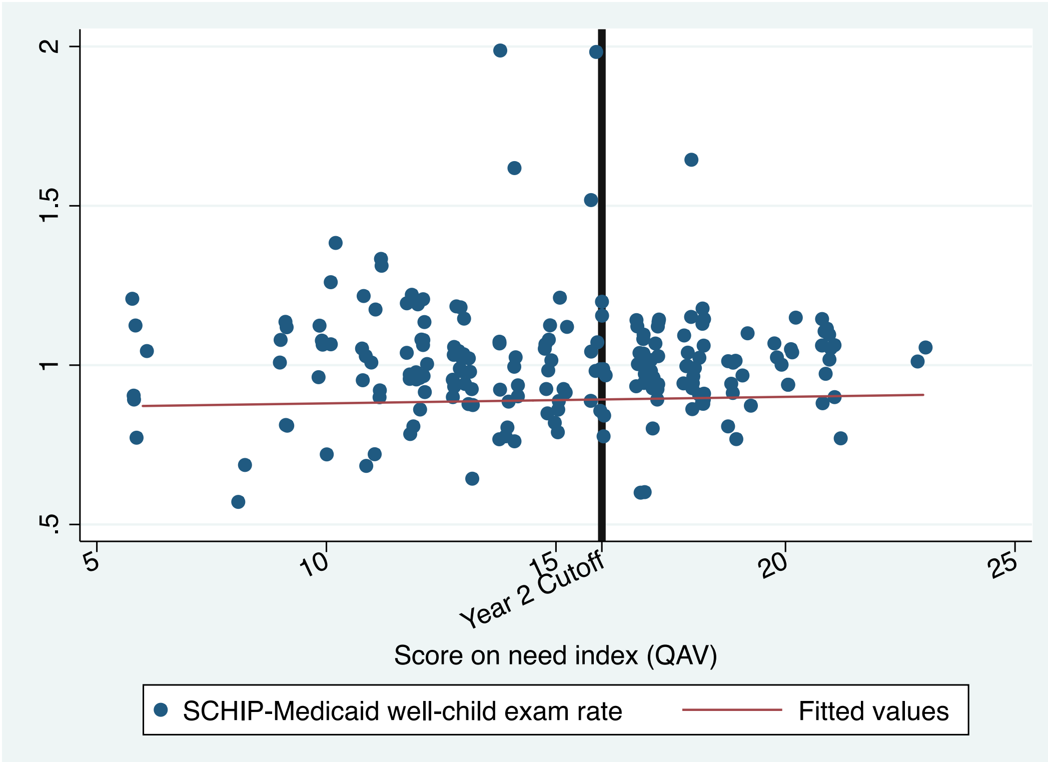


FIGURE 1.4 (A): GRAPHICAL ANALYSIS OF THE QUANTITATIVE ASSIGNMENT VARIABLE (QAV) ON COUNTY-LEVEL WELL-CHILD EXAM RATES

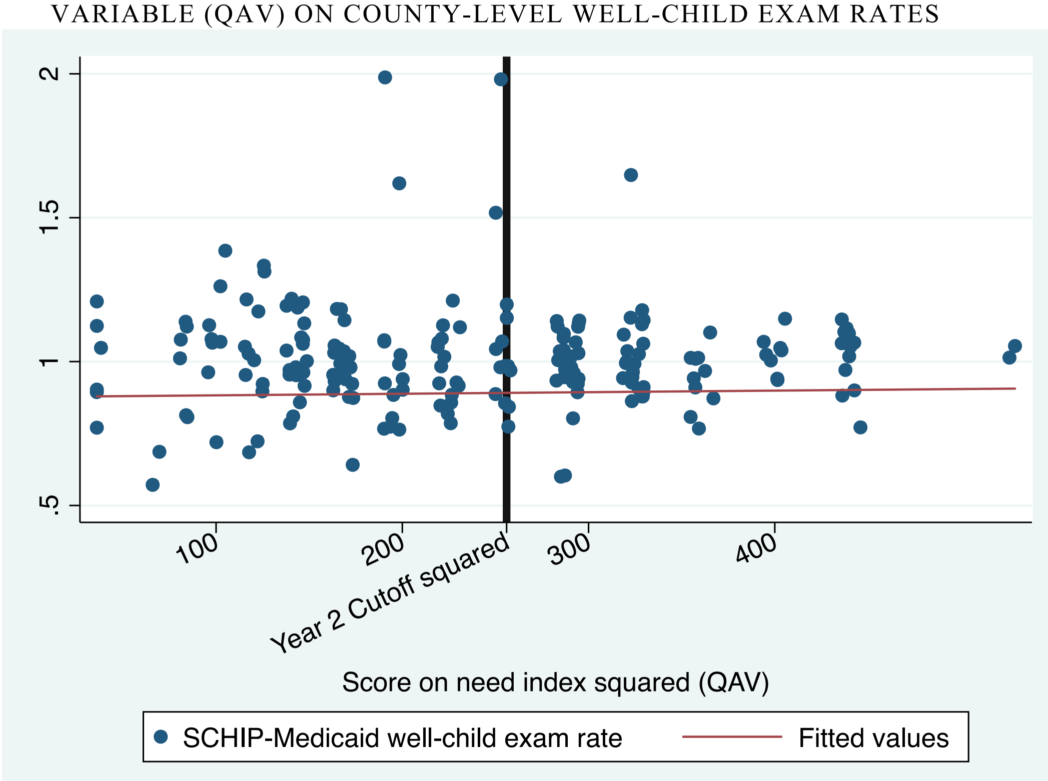


FIGURE 1.4 (B): GRAPHICAL ANALYSIS OF THE QUANTITATIVE ASSIGNMENT VARIABLE (QAV) SQUARED ON COUNTY-LEVEL WELL-CHILD EXAM RATES

CHAPTER 2. THE EFFECT OF STATE POLICY GOVERNANCE ON EARLY CHILDHOOD OUTCOMES

Introduction

A central and hotly contested idea among public management theorists is the concentration of governance (Kettl, 2000). *Vertical* governance refers to the extent that agencies are set up hierarchically and control is more centrally concentrated. *Horizontal* governance is defined as dispersing the control, responsibilities and services across agencies. While there is a wealth of scholarly discussion regarding the justifications for vertical and horizontal governance, little is known about the relationship between governance and effective policy management or to improved outcomes for the target populations of policies.

Early child care and education (ECCE) is a primary example of a policy field where there are both vertical and horizontal governance structures at the state-level. Over the past 30 years, states have become increasingly involved in policies and activities that focus on the well-being of young children. As a result, states developed institutional structures with very different characteristics for providing and coordinating the disparate programs for children ages birth to five years, including the concentration or dispersion of governance. There are now 50 different variations of child policy governance in the U.S. A striking difference is in the number of agencies involved: 13 states have 4 or more different agencies involved in ECCE, yet some states like Maryland and Georgia now have one agency that governs all child policies and programs.

The horizontal dispersion of programs across agencies is widely criticized by child developmentalists, advocates, policy scholars, and practitioners who describe the child policy field as ‘fragmented’ (Bruner, Stover Wright, Gebhard, & Hibbard, 2004; Kamerman & Kahn, 2001; Lombardi, 2003). Child policy is a relatively new policy area for states and the governance of ECCE was not necessarily deliberate or well-planned; programs and policies have been somewhat unmethodically layered or merged onto existing state institutions such as social services, workforce supports and departments of health (Barnett, Friedman, Hustedt, & Stevenson-Boyd, 2009; Kagan & Kauerz, 2012). A typical state situation may be that a department for employment support administers subsidies for child care, a department of education administers the state’s pre-kindergarten (pre-k) program, and the department of health is responsible for the licensing and regulation of all ECCE providers. Critics hypothesize that this ‘agencification’ or dispersion of policies across departments is detrimental to service delivery and child outcomes, and that centralized or integrated policy governance in ECCE would improve children's well-being. Howes and Pianta (2009) convey the sentiment of these criticisms: “the haphazard funding, monitoring, and programmatic organization and infrastructure supporting efforts to foster young children’s developmental competencies in various settings undermines the capacity to deliver on that promise” (p. xix).

On the other hand, there are advocates of a multiple-agency approach, like those of the New Public Management school, who theorize that bureaucracies should be disaggregated into smaller, more manageable units which can redistribute power, enhance efficiency, and stimulate innovation (Barzelay, 2001; De Vries, 2000; Hood, 1991; Neuman, 2005; Weiler, 1990). In this style of management, coordinating across diverse agencies and using market-based approaches to policy implementation theoretically results in better services. There is even some evidence from other policy fields indicating that consolidated or integrated services management does *not* produce better client outcomes, which may support the decentralized approach (Bickman, 1996; Jennings & Ewalt, 1998). A tenant of New Public Management is that interagency coordination and organized divisions of labor are essential to optimize program and policy performance.

Arguments—both theoretical and practical—suggest that governance over children's policies matters, but we have little evidence about whether differences in governance affect children's well-being. Meanwhile, some states have taken action to eliminate fragmentation and bring all of their early childhood programs into one central agency. These changes are occurring without knowing if consolidating governance will have any impact on children. In addition, many other states now have some type of short-term governance bodies such as children's commissions to link these disparate agencies in light of these theories. There is some evidence indicating that both administrative consolidation and interagency coordination have differential, albeit limited, effects on policy outcomes (Grubb & McDonnell, 1996; Jennings & Ewalt, 1998; Lynn, Heinrich, & Hill, 2001). Still, policy changes at more distal links in the causal chain of program intervention may not affect individual child well-being.

Motivated by these unresolved ideas about the substantive effects of vertical and horizontal structures, the differences in state ECCE governance present a unique opportunity to assess whether one of these approaches actually results in children being better off. Most research on governance is hierarchical even though scholars are quite vocal about how integration, coordination, and collaboration and issues of horizontal governance are critical (C. J. Hill & Lynn, 2005; Kettl, 2000). And there are no studies that look at the effects of governance on children ages zero to five, a time period where the effects of poverty—the problem that many of these programs are trying to address—are more profound that at any other developmental period (G. J. Duncan, et al., 2007; Grissmer & Eiseman, 2008; Heckman, 2008). Therefore, the question of whether differences in state policy governance have consequences for young children is an important one.

This study takes a look at one particular aspect of state policy governance, policy dispersion, to see if and how it affects children's cognitive and physical development in early childhood. To be sure, estimating the causal effects of child policy governance is challenging because policies are not randomly determined; rather they are a function of a states observed and unobserved characteristics. We address potential endogeneity of state policy decisions using Instrumental Variables Estimation and a unique nationally representative, longitudinal dataset of young children merged with rich state-level data.

Background

There has been increasing public concern with child well-being since the 1930s due to changes in female participation in the workforce and the growing acceptance that children's cognitive and social skills are actually malleable—rather than fixed traits—and are amenable to policy intervention. The federal government began funding child care during World War II based on the needs of adult workers and women entering the workforce during wartime, evolving to the present day, where federal spending on children's programs comprises 7.9% of total spending (Isaacs, Toran, Hahn, Fortuny, & Steuerle, 2012). The proportion of mothers working outside of the home also drastically increased during the 1970s, as did women's educational attainment (Waldfogel, 1998). Today, nearly 64% of mothers with children ages 5 and under are in the labor force, compared to 29% in 1970 (ChildCare Aware of America, 2012; Hofferth & Phillips, 1987).

Also during this time, copious research findings from neuroscience, psychology, education, and economics converged, to provide strong empirical justification for the role of early childhood development and education programs for healthy child development, and the importance of early intervention in preventing long-term problems, particularly for children in poverty (Barnett, 2011; Bowman, et al., 2000; Hackman & Farah, 2009; Heckman & Masterov, 2007; Kirp, 2007; Magnuson & Waldfogel, 2005; McLoyd, 1998; NICHD Early Child Care Research Network, 2005; Peisner-Feinberg, et al., 2001; Sameroff, 2010; Shonkoff & Meisels, 2000; Shonkoff & Phillips, 2000). This is because the brain is extremely responsive to early life experiences that facilitate or interfere with neural connectivity (Fox, et al., 2010; Hess, 1973; Knudsen, 2004; Levitt, 2008; Singer, 1995; Trachtenberg & Stryker, 2001). This research and the widespread recognition that early life experiences could shape children's abilities and well-being further influenced policy via strong efforts from advocacy groups, private foundations, and the business sector (Adams & Rohacek, 2002; Blau & Currie, 2004; Goldsmith & Meyer, 2006; Kirp, 2007; Loeb, Fuller, Kagan, & Carrol, 2004; Zigler, Gilliam, & Jones, 2006).

Along with the changing political forces of the time, these ideas dramatically shifted the U.S. public opinion of spending on young children, putting pressure on the government to take on a greater, more proactive role in providing for their well-being (Bushouse, 2009; Clifford & Crawford, 2009; S. S. Cohen, 2001; Warner, 2007). This is especially true for low-income children. Public programs use ECCE to counteract and compensate for the detrimental effects of family poverty on child development (Brooks-Gunn & Duncan, 1997; Gormley, et al., 2005; Howes, et al., 2008; Shonkoff & Phillips, 2000). In this way, early child care and education (ECCE) policy highlights the conflicting cultural ideas about who is responsible for the well-being of young children because it straddles the divide between education and care; the former is more broadly accepted as a public responsibility, and the latter as a private one (Pianta & Howes, 2009; Rose, 2010). Nevertheless, there now are numerous policies and programs for children ages birth to five years spanning health, labor, welfare, and education in federal, state, and local government (Gormley, 2007; Kagan & Rigby, 2003; Kauerz, 2008; Waldfogel, 2006b). States, however, are at the forefront of child policy.

Child policy at the state level

Though the federal government is central to funding policies targeting children and their families, state government has become the most active locus for developing and implementing child policies (Zigler, et al., 2006). Direct state-level involvement in early childhood policy (and other fields) emerged through two primary mechanisms: the devolution or decentralization of federal programs and state-level innovation and development. *Devolution* was initiated by the intergovernmental reform styles of the 1970s through the 1990s, where policy changes were affected by the Republican agenda for federalism and the transfer of power to the states by the use of state block grants (Conlan, 1998; Kettl, 2000; Nathan, 1996). This gradually transferred more responsibilities to the states for public programs targeting young children and their families such as social welfare programs (e.g., Temporary Assistance to Needy Families (TANF)), and early intervention and special education services for children with disabilities through the Individuals with Disabilities Education Act (IDEA)(Conlan, 1998; Kagan & Rigby, 2003; Lombardi, 2003; S. J. Meisels & Shonkoff, 2000; Sandfort, 2010). In 1996, the Personal Responsibility and Work Opportunities Reconciliation Act (PRWORA) welfare reform legislation marked a critical departure for state policy because it fully devolved the authority over the major welfare policies to the states (Fellowes & Rowe, 2004; Kamerman & Kahn, 2001), and children were major beneficiaries of these policies (Meyers, Gornick, & Peck, 2001).

The federal government retained a substantial amount of influence, but states had enough control to change the major dimensions of welfare programs including: benefits available to families, program sanctions, time limits, and requirements for eligibility (Blank, 2002; Capizzano & Adams, 2000; Heclo, 1997; Kamerman & Kahn, 2001; Martinson & Holcomb, 2002; Meyers, et al., 2001; Meyers, Gornick, & Peck, 2002; Soss, Schram, Vartanaian, & O'Brien, 2001). These changes are especially consequential for early childhood policy; two of the largest welfare programs, Child Care and Development Fund (CCDF) and Temporary Assistance for Needy Families (TANF), account for more than one-third of the total amount of money the federal government spends on children under age five ($14 billion in 2012) (General Accounting Office, 2000a; Isaacs, et al., 2012). These programs subsidize the substantial cost of child care and education for low-income and working-poor families. Combining CCDF, TANF, and federal Head Start spending with state spending on pre-kindergarten (pre-k) programs amounts to nearly $16 billion annually in benefits and services for preschool-aged children alone (ages 3-5 years)(Schultz, 2009). These programs have continued to evolve with states playing a major role in policy administration and implementation.

A central component of children's policy is ECCE. Because education has been a state responsibility historically, state-*developed* policies for young children focus primarily on ECCE. States and communities determine the development, funding, administration, and regulation of ECCE programs, with some federal involvement and a strong private-sector role (Chase, Dillon, & Valorose, 2008; Children's Defense Fund, 2004; Clifford & Crawford, 2009; Kagan & Rigby, 2003; Pianta & Howes, 2009; Zigler, et al., 2006). These include subsidized child care, early childhood intervention programs for children with disabilities, pre-k, home visitation, and statewide collaboration of Head Start programs. State government is centrally involved in implementing child care and pre-k; every state manages the regulation of child care and the administration of federal subsidies (through CCDF and TANF), and 39 states have created their own pre-k programs (Hustedt & Barnett, 2011).

Since states have initiated many ECCE policies on their own, the dimensions or characteristics of ECCE programs vary extensively between states (Barnett, et al., 2009; Doherty, 2002; Gilliam & Ripple, 2004; Kagan & Rigby, 2003; Lombardi, 2003; Pianta & Howes, 2009). There are various pockets of literature that examine ECCE state policy characteristics, many of which are critically important for child and family outcomes. Some of the major dimensions include: program eligibility (Barnett, et al., 2009; Blau, 2001; Clifford & Crawford, 2009; Stebbins & Knitzer, 2007), spending (Barnett et al., 2010), licensing and regulation (Clifford & Crawford, 2009; Gormley, 1999), assessment for school readiness and academic outcomes (Kagan, Moore, & Bredekamp, 1995; Love, 2001; S. Meisels, 1998; Roberts, Innocenti, & Goetze, 1999; Saluja, Scott-Little, & Clifford, 2001), accountability (Harbin, Rous, & Mclean, 2005), length of day and year (Barnett, et al., 2009), quality of care, the assessment of quality (Harms, Clifford, & Cryer, 1998; Mashburn et al., 2008) and the development of Quality Rating and Information Systems (Tout, Zaslow, Halle, & Forry, 2009), curricula (Ritchie & Willer, 2008), learning standards (Scott-Little, Kagan, & Frelow, 2003; Scott-Little, Kagan, & Frelow, 2006; Scott-Little, Lesko, Martella, & Milburn, 2007), teacher credentials and training (Clifford & Crawford, 2009; Early et al., 2007), service delivery (Halpern, 2000; Kamerman, 2000; Sandfort, 2010), and the provision of additional comprehensive services (e.g. vision screening) (Brooks-Gunn, 2003; Gormley, 2007). In addition, states set the age at which school becomes compulsory, ranging from 5 to 8 (Cryer & Clifford, 2003). Even with all the research attention on these issues, another major dimension along which states vary, policy governance, remains unexamined.

Governance of ECCE policy

Governance is the way that governments organize, administer, and implement policies and services through the allocation of responsibility for decision-making and the delivery within and across administrative departments, levels of government, and public and private actors (Gormley, 1996; Kagan & Neuman, 2005; Kamerman, 2000; Neuman, 2005). The systems and structures that form governance are important for the management and performance of public agencies (Barzelay, 2001; Bozeman, 1993; Gormley, 1987; Heinrich & Lynn, 2000; Kettl, 2000, 2005; Lynn, 1994; Lynn, Heinrich, & Hill, 2000; Weaver & Rockman, 1993; Wildavsky, 1979). Different governments have developed very different strategies for the management, institutional design, and governance of ECCE programs, notwithstanding their similar goals, characteristics, and funding strategies (Barnett, et al., 2009; Kagan & Rigby, 2003; Neuman, 2005; Waldfogel, 2006a). Internationally, the structure of early childhood policy management and governance varies extensively between industrialized countries (Kamerman, 2000; Neuman, 2005; Organization for Economic Cooperation and Development (OECD), 2001). One of the most controversial characteristics of state ECCE governance is the dispersion of authority for these programs across agencies and organizations.

Policy Dispersion

Policy dispersion refers to the concentration of governance across disparate departments, offices, or agencies. An assessment of ECCE governance by the Government Accountability Office showed that there were 69 federal programs across nine different federal agencies that provided or supported education and care for children under five years (2000a). Figure 1 illustrates this dispersion of programs across agencies. States have tended to follow the federal government in this regard, dispersing authority and responsibility for children's well-being across multiple organizations.

There is considerable variation in how the responsibility and administration of ECCE programs are assigned across states (Kagan & Rigby, 2003; Kamerman, 2000; Kauerz, 2008; Mitchell & Stoney, 2008). Multiple government agencies are responsible for the core components of state ECCE policy such as program funding and ECCE provider reimbursement, teacher certification, licensing and regulating child care providers, child registration, and monitoring program standards (Barnett, et al., 2009; Kagan & Rigby, 2003; Kamerman, 2000; Kauerz, 2008; Mitchell & Stoney, 2008; Neuman, 2005; Waldfogel, 2006a; Witte & Trowbridge, 2005). As the ECCE policy field evolved, programs developed independently of one another were either layered or merged onto existing state institutions such as social services, workforce supports or departments of health, or states created an entirely new governing body for programs (Barnett, et al., 2009). For example, six different agencies are involved in ECCE program administration in Texas, whereas Maryland has consolidated all of the ECCE functions into one agency.

While state control of institutions may offer opportunities for innovation, ECCE governance evolved for the most part without an intentional strategy to create a policy system for the age group. This has placed some of the core components of ECCE into structural siloes, including different legislative committees and state departments (Chase, et al., 2008; Sandfort, 2010). There is also a 'parallel play' of programs that occurs when agencies in disparate structures don't know what other agencies are doing and multiple agencies provide similar services (Gallagher & Clifford, 2000). In addition, the provision of ECCE frequently includes market-based delivery of services through nonprofit and private for-profit organizations, further increasing the dispersion of policy administration and implementation (Barnett, et al., 2009; Hood, 1991; Kettl, 2000, 2005; Nathan, 1996; Salamon, 2002; Sandfort, 2010; S. R. Smith, 2010).

This extensive state-level variation both in governance and in program characteristics illustrate why top early education scholars describe ECCE policy as a "stunning cacophony of regulation; competing aims; blended funds; and lack of coherence in program design, curriculum, and staffing with many programs spending precious dollars, time, and staff attention on simply managing and processing all the paperwork" (Pianta, Barnett, Burchinal, & Thornburg, 2009, p. 54). A patchwork of programs, funding mechanisms, and services that vary among states, cities, and communities exist to implement ECCE policies; it includes a combination of public and private institutions, governmental and academic leadership, as well as a diversity of program strategies, and traditions; all of which have been shaped by family demand and government initiatives (Clifford & Crawford, 2009; Halpern, 2000; Pianta, et al., 2009; Stoney, Mitchell, & Warner, 2006). Put another way, many scholars characterize the American early childhood policy landscape as 'fragmented' (Gallagher, Clifford, & Maxwell, 2004; Kamerman & Kahn, 2001; Lombardi, 2003; Meyers, 1993). These frustrations with complexity and symptoms of fragmentation in ECCE policy denote matters of policy management, governance, and institutional design and therefore warrant attention from policy researchers.

Policy dispersion and child outcomes. Regardless of whether or not child policy is fragmented, the important question is whether or not the spread of policies across different state agencies affect policy outcomes at the child- and family-level. The general mechanism linking governance to child outcomes is that by changing the management and administration of policies at the state-level, governance could affect the quality or quantity of services that children and families receive and experience. The governance effect could also be transmitted through ECCE providers if governance influenced the regulation and quality control of ECCE. Speculations of whether dispersion has a negative, positive or null influence on children's well-being varies across different disciplines and bodies of research.

When policy administration and service provision are dispersed across agencies, this could mean different: entry points into service systems, eligibility requirements, professional philosophies and structural boundaries (Hodges, Nesman, & Hernandez, 1999; Kagan & Kauerz, 2012; Meyers, 1993; Rivard & Morrissey, 2003). Thus the fragmentation of governance may be detrimental to child well-being if it makes it harder for parents to navigate the system and know which services and programs are available for their child (Adams, Snyder, & Sandfort, 2002; Dunleavy, Margetts, Bastow, & Tinkler, 2006), or if it contributes to disruptions in children's care such as lack of coverage, changes in providers, or fewer quality controls (Gallagher, et al., 2004; Kagan & Rigby, 2003; Kauerz, 2008; Lombardi, 2003; Stoney, et al., 2006; Witte & Trowbridge, 2005). For example, in a number of states different agencies are responsible for Part C of IDEA (ages birth to 3) and Part B of IDEA (ages 3+, including section 619 for preschool programs), jeopardizing the transition and continuity of intervention services for young children with disabilities as they age (Gallagher & Clifford, 2000).

If the dispersion of state-level governance results in more transitions between schools, child care providers, or other service providers, then dispersion may be detrimental to children's development. 'Turbulence' or instability in childhood, like changing schools or teachers, can have a negative affect on a child's social and behavioral outcomes because children need a stable and continuous set of services for optimal development (Adams & Rohacek, 2010; Howes, 1988; Howes & Hamilton, 1993; Loeb, et al., 2004; Moore, Vandiviere, & Ehrle, 2000; Morrissey, 2009; Stoney, et al., 2006; Tran & Winsler, 2011; Witte & Trowbridge, 2005). This may be because the teacher-child relationship is central to positive child development (Bredekamp, 1997; Burchinal et al., 2008; Howes & Ritchie, 2002; Howes, Whitebook, & Phillips, 1992). Additionally, having dependable, quality, and affordable care is related to family work stability and economic well-being (Capizzano & Adams, 2000; Han & Waldfogel, 2001; Moore, et al., 2000).

Another way that dispersion may negatively affect policy implementation or make policies less effective in improving child outcomes is there are few, if any, statewide coordinating data systems.[10] Right now, multiple agencies track information about the same children. No data coordination to connect disparate programs makes it difficult for families to access complimentary services for their children, for service providers to understand children's needs and connect them to other available resources, and for policymakers to understand the state's needs and manage public resources (Dunleavy, et al., 2006; Gitterman, 2010; Gruendel & Stedron, 2012; Regenstein, 2010; Roberts, et al., 1999). And even though

[10] It should be noted that the privacy issues associated with coordinating detailed child and family data across state agencies and private providers are considerable. See Greundel & Stedron (2010) for a brief discussion.

programs within the field target children of the same age, many target specific populations *within* the age group so these services can be uncoordinated and sometimes redundant (Gallagher & Clifford, 2000; Gallagher, et al., 2004; Kauerz, 2008; Konrad, 1996; Meyers, 1993). For example, if a child receives services through IDEA and also attends Head Start or pre-k, they may undergo multiple developmental screenings, have multiple eligibility determinations, and separate program-related health care providers.

For these reasons, the dominant hypothesis among child development researchers, child advocates, and government agencies is that centralized, consolidated, or integrated governance of ECCE would improve children's well-being and that fragmentation is detrimental (Bruner, et al., 2004; Kagan & Kauerz, 2012; Lombardi, 2003; Maternal and Child Health Bureau, Administration, & Services; Rose, 2010). This is reflected in both the campaigns for early childhood systems from advocacy organizations (e.g. BUILD Initiative; Birth to Five Policy Alliance), and from federal initiatives for system-building across early development sectors (e.g. Maternal and Child Health Bureau's Early Childhood Comprehensive Systems grant program, Race To the Top-Early Learning Challenge fund). Some states have brought all of their early childhood programs into one central agency, such as Pennsylvania's Office of Childhood Development, or Georgia's Department of Early Care and Learning. There are now also short-term governance bodies such as commissions and gubernatorial children's cabinets in more than 30 states, but they possess very little authority to directly influence policy (Grubb & McDonnell, 1996; Kagan & Rigby, 2003; Kauerz, 2008).

On the other hand, there is some evidence to suggest that consolidating or integrating government services would *not* necessarily translate into children's well-being.

The dispersion of service delivery has received some examination in the children's mental health services and job training and vocational education policy fields. In a large demonstration study of children's mental health service delivery, a consolidated or 'systems-of-care' approach improved the continuity of care, client satisfaction, and access to a fully array of care services (at a higher program cost), but did not affect children's clinical outcomes relative to the comparison delivery approach (Bickman, 1996, 2002). Other system-of-care research indicates that the consolidated service providers were not able to improve service quality, delivery, and coordination effectively (Heflinger & Northrup, 2000; Vinson, Brannan, Baughman, Wilce, & Gawron, 2001). It is possible that a reform at the system-level distracts from the focus on developing and implementing the most effective children's services; in the end, just affecting the service delivery structure did not appear to impact children (Salzer & Bickman, 1997).

Another hypothesis is that the dispersion of programs or services across agencies is not in and of itself a problem; it is coordination that could be the problem. Some research shows the differential and limited effects of administrative consolidation and interagency coordination on policy outcomes (Grubb & McDonnell, 1996; Jennings & Ewalt, 1998; Lynn, et al., 2001). Consolidation or integration is one way of cultivating coordination amongst programs, but it does not necessarily mean that services will actually be coordinated (Jennings, 1994; Jennings & Ewalt, 1998; Martinson, 1999). Research examining the coordination of job training and education programs highlighted that agency consolidation did not necessitate successful coordination across units (Jennings, 1994; Jennings & Ewalt, 1998). Even if all programs reside in a single agency or are co-located, the coordination between complex policies, organizations and programs is still challenging for administrators, managers and front-line staff (Meyers, 1993). There may also be gains from specialization in having multiple agencies. Both formal and informal coordination mechanisms allowed job training providers to maintain a well-defined division of labor between multiple agencies at the city-level, and not through a centralized dominant institution (Grubb & McDonnell, 1996). Agency administrators and staff also identify leadership as more important for coordination than the consolidation of authority in these studies (Huxham & Vangen, 2000; Jennings, 1994).

There are many different ways that states govern ECCE services; one state may be fragmented or dispersed and another may have a more consolidated or centralized approach. Yet no one knows which is actually best for children, or if children are even affected. In this paper we aim to fill this gap in the empirical research and examine the extent to which cross-state variations in the dispersion of ECCE policies across state agencies affect child well-being. In the next section we describe some of the theoretical rationales of state preferences for single- or multiple-agency approaches.

Theoretical rationales for policy governance

There is a vast literature with well-developed theories about policy management that one can bring to bear on the issue of concentrated versus dispersed governance. The relevant work comes from economics, political science, and public administration and offers several explanations and theoretical bases for the current state of management and governance in ECCE policy.

The theory of *New Institutionalism* hypothesizes that political institutions shape the rules of the policy environment, thus shaping policy decisions and future policy trajectories (March & Olsen, 1984; Steinmo & Watts, 1995). These institutions influence how interests organize, how much access and power they can have, what positions they side with, and give priority to certain ideas and groups over others (S. S. Cohen, 2001; Hall & Taylor, 1996). Here, policies themselves become institutions that structure their distribution of resources, agency, authority, and legitimacy (Rigby, Tarrant, & Neuman, 2007). This means that different policies generate disparate structures with separate rules and political fates, which is exemplified in ECCE. As noted, the development and expansion of CCDF, Head Start and pre-k over the past 20 years came from increasing awareness about the importance of child care in helping low-income parents work, along with research about the importance of early education for development. However, these services developed as separate policy areas with different objectives and funding structures, creating a conceptual division between policies with overlapping purposes (i.e. child care and education) (Adams & Rohacek, 2002; Brauner, Gordic, & Zigler, 2004; Lamb, 1998). And while the debates surrounding Head Start are often hotly contested, pre-k has widespread and increasing political favor (Barnett, et al., 2010; Bushouse, 2009; Henry, Gordon, & Rickman, 2006; Zigler & Styfco, 2004). This institutional separation of policies not only makes it more difficult for parents to access a policy's services for their child (e.g. due to multiple clearance points into service systems, different eligibility requirements for programs, etc.), but also would hypothetically decrease each individual policy's stability in the long-term.

The processes that influence the creation of policy structures are critical because policy designs have a significant 'institutional stickiness' to them, making it difficult to change course once an institutional arrangement is established (Rigby, et al., 2007). *Historical Institutionalism* asserts that once institutions are in place, the notion of 'path dependency' makes it extremely costly to deviate from the status-quo, and policies then become self-reinforcing and perpetuate through a positive feedback process (Levi, 1997; Pierson, 2000). Specifically, policy feedback describes how enacted policies and subsequent institutions 'create a new politics', where the next rounds of policy making are constructed and nurtured by feedback from the initial policy decisions (Pierson, 1993; Schattschneider, 1935; Skocpol, 1992). By proliferating institutions for children's policies, diverse political interests can gain influence and obtain resources to distribute in ways that benefit their key constituencies; by concentrating agencies, *existing* political interests obtain more resources for their purposes. From this perspective, Cohen argues that political institutions and organized interests have shaped the politics and outcomes of child policy resulting in the fragmented governance of child care public policies; furthermore, this has negatively affected the subsequent political support of ECCE in the U.S. (2001).

From the organizational theorists, Moe's theory of public bureaucracy explains that the design of our public institutional or bureaucratic structure is "inextricably bound up in politics" (1991). Elected leaders and different players in public bureaucracy support governance structures that suit their different interests and constituencies. The resulting bureaucracy is evidence of the political struggles between the chief executive, legislature and interest groups and professional groups. Moe describes the consequences:

> "Public bureaucracy therefore cannot bear much resemblance to the rational organization of the new economics. Winning groups, losing groups, legislators, and presidents combine to produce bureaucratic arrangements that, by economic standards, appear to make no sense at all. Agencies are not built to do their jobs well. Strange and incongruous structures proliferate. Presidential bureaucracy is layered on top of congressional bureaucracy. No one is really in charge" (1991, p. 148).

Here, each government agency is a structural reflection of its own politics, perhaps to its detriment. Based on Moe's theory the present fragmentation of ECCE governance is both unsurprising and inevitable. Still, it is unclear whether the resulting structure would be consequential to client outcomes.

In spite of this irrationality of government organization, one can describe the parameters of bureaucracy and governance in a simple way. Kettl (2000) characterizes the institutional locus of control in two dimensions—vertical and horizontal. *Vertical* refers to the extent that agencies are set up hierarchically. *Horizontal* is the extent that responsibilities or services are dispersed across agencies. This also includes the coordination and integration of service provision between bureaucratic actors, including the links between governmental agencies and between governmental and nongovernmental agencies. In this way, the perceived problem of fragmentation or dispersion of governance in ECCE programs can be viewed as a question of whether more vertical (i.e. concentrated) or horizontal (i.e. dispersed) governance is more effective at influencing policy outcomes, if it bears any influence at all.

The broad literature of the *New Public Management* (NPM) presents a rationale for a positive effect of dispersion or horizontal governance. This is because of NPM's scholarly focus on collaborative, interagency, or associational functions (C. J. Hill & Lynn, 2005; Kettl, 2000; Salamon, 2002). Emerging as a dominant public management doctrine among many industrialized countries during the 1980s, NPM sprang from the new institutional economics and the idea that the public sector can be improved by incorporating business-type practices and values (Barzelay, 2001; Hood, 1991, 1995; Pollitt & Bouckaert, 2011). Though the features of NPM are broad, one of the macro themes of this approach was *decentralization*, where public service bureaucracies were disaggregated into smaller, arguably more manageable units, with the justification that it would redistribute power, increase efficiency, and enhance learning (Barzelay, 2001; De Vries, 2000; Hood, 1991;

Neuman, 2005; Weiler, 1990). This is characterized by: ‘agencification’ or ‘hollowing-out’ of government services, marked increases in contracting and privatization through quasi-governmental agencies and nonprofits, decoupling policy systems and separating administration from service delivery, decreasing hierarchical organization, devolving decision-making to states and localities, and using block grants to states (Dunleavy & Margetts, 2010; Dunleavy, et al., 2006; Kettl, 2000; Rhodes, 1996). The use of the nonprofit and private sectors and the provision of services through a mix of third-party actors is especially prevalent in social welfare policy fields, particularly in ECCE (Barnett, et al., 2009; Kettl, 2000, 2005; Nathan, 1996; Salamon, 2002; Sandfort, 2010; S. R. Smith, 2010). This work highlights the fact that in the modern age of governance, “central government is no longer supreme” (Rhodes, 1996, p. 657).

As a result, decentralization increased the need to understand how policy actors coordinate work across several single-purpose agencies (Ling, 2002; Rhodes, 1996). This presupposed the scholarly focus on intergovernmental management, also known as collaborative governance, service integration, interagency collaboration, collaborative public management, ‘joined-up governance’ or holistic governance (Agranoff & McGuire, 2004; Bardach, 1998; Huxham, Vangen, Huxham, & Eden, 2000; Ling, 2002; Pollitt, 2003; Rhodes, 1996). Indeed, coordination is an age-old issue in the study and practice of public management (North, 1990; Pollitt & Bouckaert, 2011). This literature deals with facilitating and operating multi-organizational arrangements and aligning the activities of separate organizations towards policy goals (Agranoff & McGuire, 2004; Ling, 2002).

Critics argue that NPM exacerbated the complexity and opacity of government, making service delivery worse overall by: increasing the number of clearance points required for policy access and authorizations, weakening citizens problem-solving competence, reducing the accessibility of public services, and increasing the scope for buck-passing and denial of responsibility (Dunleavy & Hood, 1994; Dunleavy, et al., 2006; Hood, 1991; Pollitt & Bouckaert, 2011). One might argue that the present ECCE governance is akin to Dunleavy & Hood's "headless chicken" management outcome of NPM, common in fragmented sectors in the US (2004). In this 'no-one in charge' management model, organizations are over-managed at the individual level but under-managed overall because there are no *system*-wide rules of procedure. This is compounded by significant private and public sector separation and differences in operations (Dunleavy & Hood, 1994). In the end, critics claim that the justifications for decentralization were merely political, services were not integrated, and efficiency was not improved (De Vries, 2000; Hood, 1991; Weiler, 1990).

If NPM-style governance via decentralization made interagency coordination too difficult, this may give credence to a more concentrated governance approach. Yet one could also argue that if services were overly concentrated, the monopoly of policy provision could stifle innovation and reduce the control and discretion of front-line staff and lower-management in helping families. Furthermore, vertically structured organizations may allocate more resources towards senior-level managers and become too 'top-heavy' to effectively serve clients. This highlights another important point about governance—it is inseparable from the economics of policy. State-level policy expenditures and the allocation of resources within and across agencies likely play a central role both in the structure of governance and in the overall effectiveness of policies. Makers and researchers of policy will be concerned with both the outcomes of governance and the costs associated with dispersion and consolidation.

In many ways, ECCE is a relatively ideal area for testing the competing theories outlined here. As these perspectives suggest, state-level politics, economics, and interorganizational networks affect policy implementation by way of governance. But theory alone is insufficient to determine whether policy dispersion has an impact on child development, or any policy outcome; empirical research is necessary to understand the implications of policy governance for outcomes.

Causality and state policy research

Examining whether differences in state ECCE governance have an impact on child development is important for many reasons. There are several theoretical and practical arguments from multiple disciplines both for and against the dispersion of policies across agencies. The only way to reconcile these competing ideas is through empirical work, which is what we do in this paper.

However, state policy research is challenging because policies are not randomly determined; they are a function of a states observed and unobserved characteristics. We have already described how the factors of states' political environment could influence both policy outcomes and their preferences for concentrated or dispersed governance. Devolution and decentralization gave state governments the political freedom and discretion to develop a structure of public programs. However, state policymakers rarely have time to rationally evaluate all possible options within the complex political, social, and economic environment (Berry & Berry, 1990; Walker, 1969). Policymakers are 'boundedly' rational; their analysis of choices is based on a set of assumptions and preferences constrained by funding, time, imperfect memory and calculation capacities, and other political interests and policy entrepreneurs (Becker, 1962; Mintrom, 1997; Simon, 1978). Although we see the outcomes of these decisions, we do not know the decision-making *process* that led to the observed choices (Simon, 1978). This unobserved process is concisely summarized by Meyers, Gornick, and Peck in a study of the effects of welfare reform on child well-being: “Social policy choices reflect the compromises, tradeoffs, partisan competition, bureaucratic maneuvering, and general messiness of incremental policy formation. Although often uncoordinated, state decisions nevertheless produce a final package of policies that reflects their exercise of political discretion” (2002, p. 459).

The analytical problem stems from the fact that the policymaker’s choices are the result of a complicated set of factors, some of which can be observed by the analyst, and some of which that cannot. We can observe the number of agencies that are responsible for children’s policy but it is more difficult to observe all the factors that influenced that decision. For example, politically conservative states are less likely to have preschool programs (Karch, 2010), and also have less stringent child care regulations (Rigby, 2007). These states may therefore differ in other important unobserved ways that affect both child policy decisions and statewide child well-being. When these unobserved factors also affect the outcomes of a given policy they confound the relationship between the policy treatment and the outcome, causing omitted variables bias. This is the primary challenge to causal inference in state policy adoption and outcomes research.

Present study

In this paper, policy endogeneity results from the fact that the unobserved characteristics of a state may be correlated with both their *governance* of child policies *as well as* their state’s child outcomes. Indeed, the hypotheses from the literature described above suggest that institutions both reflect and cause policy outcomes. While the dominant hypothesis seems to be that more horizontal dispersion in state ECCE governance will have a negative effect on early childhood outcomes, there are also compelling ideas about why more vertical or concentrated approaches may be detrimental to policy outcomes. Therefore, state ECCE policy presents an opportunity to test these competing ideas and to provide an *empirical* basis for the effects of governance on policy outcomes.

We address the possibility of state policy endogeneity using Instrumental Variables Estimation using numerous state-level social, economic, and political characteristics to instrument for policy dispersion. The outcome analyses use a nationally representative, longitudinal dataset of young children matched to the rich state information to analyze the effects of state-level ECCE policy dispersion on child-level cognitive and physical outcomes during early childhood. In each state, the components of state ECCE policy are dispersed across a different number of agencies or departments, ranging from one to six agencies. This between-state variation in governance structures allows us to explore whether differences in the dispersion of services for young children across state agencies influences child outcomes.

It is worth noting that while we are examining institutional structures, this paper is not an institutional policy analysis per se. Institutional policy analysis focuses on a government reform that affects institutional design (Gormley, 1987). Rather, we are conducting substantive policy analysis using institutional governance as our key independent variable. Furthermore, the primary goal of our analysis is not to examine *why* choices were made in the vein of organization theorists (e.g. why there are the given number of agencies in a state)(Allison, 1971; Moe, 1991); the goal is to see *whether these choices affect policy outcomes* at the child-level.

Data

Child and family-level

Our analysis uses the Early Childhood Longitudinal Study- Birth cohort (ECLS-B), a nationally representative sample of 10,700 children born in the US in 2001 created by the National Center for Education Statistics (NCES-IES-DOE). The data were collected using a stratified probability sampling design to construct an isomorphic composite of the population of families with young children in the US. The data consist of parent interviews (the biological mother in 99% of cases) and child assessments at approximately nine months of age and then repeated at 24 months, 48 months (four years), and during the autumn of the child's kindergarten year. The overall response rate for the study at the first wave was 76.8%.

All variables and mean values are listed in Table 2.1. Item Response Theory (IRT) was used to construct child ability measures (thetas) for each developmental outcome listed in Table 1 (reading, math, and fine motor skills). The four-year and kindergarten year cognitive outcomes (math and reading) include items from the Peabody Picture Vocabulary Test (PPVT), Test of Early Mathematics Ability (TEMA), Woodcock Johnson Tests of Achievement, Comprehensive Test of Phonological Processing (CTOPP), pre-Las, and others instruments designed by IES for the ECLS-Kindergarten Cohort (S. E. Duncan & De Avila, 1998; Dunn & Dunn, 1997; Rock & Pollack, 2002; Wagner, Torgesen, & Rashotte, 1999). Four-year-old and kindergarten fine motor theta scores are generated from the Bruininks-Oseretsky Test of Motor Proficiency and Movement Assessment Battery for Children (Bruininks & Bruininks, 2005).

State-level

State-level variables were matched to the ECLS-B sample[11] based on zip codes at each wave. Table 2.1 shows a description of each state-level variable, their data source, average values. The following section provides further explanation and justification for the selection of these variables in our analyses. We describe here our two key policy measures.

The primary policy variable in the study is the dispersion of ECCE governance. We created this variable using information collected by the National Child Care Information Center in the Office of Childcare, Department of Health and Human Services in 2008. These data represent the number of institutions in the state that are involved in the seven defined areas of ECCE policy: child care subsidy, licensing, quality initiatives, pre-k, IDEA and IDEA-Early Intervention. Appendix B lists states by their number of state-level ECCE institutions.

We took this number (1-6) and divided it by seven for states with a pre-k program, or divided it by six for states without pre-k, to create a proportionate measure of the number of agencies relative to the appropriate number of ECCE policy areas provided by the state. This formula produced a number between zero and one, giving larger values (i.e., closer to 1) to more horizontally dispersed states, and a smaller value to states with more concentrated governance. We then used the resulting number to assign states a *dispersion scale* value, between one and five, where larger values imply more dispersed governance (i.e. across more bureaucracies). We created an integer scale because the decimal point value from our initial formula would have falsely inflated the precision with which the measure was calculated

[11] It is important to note that because the NCES used sampling strategies to construct the ECLS-B so that it was nationally representative of children born in 2001, the resulting sample is not necessarily representative of individual states. Because of this, we cannot make statements about specific states, but we can generalize to children living in states with certain policies (McCarroll, 2011). Also note that children living in the District of Columbia were excluded from the analyses because of the district's anomalous characteristics and governance.

(e.g. 0.823). As a result, the interpretation of a one-unit increase in this scale in our regression results is somewhat arbitrary, but it does indicate some ordinal effects of greater horizontal dispersion of ECCE agencies. We also created a non-linear measure of dispersion as a dummy variable for states with *highly dispersed* governance (>3 on the scale). We recognize that our operationalization of governance and policy dispersion may be overly simplistic and somewhat crude and consider this attempt at measurement as exploratory.

As mentioned in the theoretical rationale section above, one cannot examine policy without considering resources. Therefore, we also include two measures of policy expenditures in our analyses. We combined total state Head Start and CCDF spending and divided this by the total number of children ages birth-12 (ages for which children are eligible to receive CCDF funding) to represent ECCE expenditures. We included only these two funding sources because IDEA allocations come directly from the federal government, pre-k is not in place for every state, and there are limited data with respect to each state's specific quality initiatives. We also include the states' per-pupil expenditure for public education, kindergarten through grade 12 (k-12), to capture the value placed on education within the state.

Methods

Econometric approaches to address state policy endogeneity

The primary challenge to the cross-state research design is overcoming the endogeneity of state policy choices. When estimating ordinary least squares (OLS) models to estimate the effects of state-level policy variations, the coefficients of interest are likely to be biased by the omission of states' unobserved characteristics, so one cannot make causal interpretations or generalizations. This is because one of the primary assumptions of OLS is that the model is fully specified (i.e. no omitted variables). OLS is biased when omitted variables are correlated with included explanatory variables, as is the case with state policy endogeneity (Kennedy, 2008). One can mitigate policy endogeneity with OLS by using a comprehensive set of covariates that capture the determinants of ECCE policy and governance based on literature and theory. This can be effective at modeling unobserved selection mechanisms and reducing bias when the true selection process can never be known (Steiner, Cook, Shadish, & Clark, 2010), but we cannot be confident about OLS coefficients being considered unbiased estimates of the effects of state-level policy variations.

Another method for dealing with unobservable state characteristics is the state fixed effect. This uses within-state variation to identify a policy treatment effect. However, to our knowledge a time-varying measure of governance to generate *within-state* changes in governance does not exist; rather, we primarily observe *between-state* variation in a somewhat fixed characteristic. Even if governance were measured over time, states would have to have changed their governance within the time period of the child-level study in order to assess its effects on individual-level policy outcomes. Without a time-varying policy variable and an adequate number of state policy changes observed during the study period, fixed effects are infeasible.

To address potential policy endogeneity, we exploit the fact that the likely endogenous regressors and outcome variables are at different levels of aggregation—the endogenous variables are at the state-level and the outcomes are child-level—presenting the opportunity to use Instrumental Variables Estimation (IVE) with an instrument or instruments at the state-level. IVE takes variation in the troublesome endogenous variable and matches it up with variation in an instrument, and uses only this exogenous variation in the instrument to estimate a treatment effect (Foster & McLanahan, 1996; Kennedy, 2008; Winship & Morgan, 1999). This removes the correlation between the troublesome variable and the error term (i.e., unobserved state characteristics) and provides a consistent estimator under key assumptions (Cameron & Trivedi, 2009). An instrument must meet two conditions: be highly correlated with the endogenous regressor (inclusion), and uncorrelated with the outcome of interest (exclusion), thereby the instrument can only affect the outcome variable through the variation it induces in the endogenous regressor (Lee, 2005). Fortunately, there are numerous state-level factors that contribute to child policy decisions and the dispersion of governance structures but would not impact individual child outcomes directly.

A weakness of the IVE approach is that the exclusion condition is untestable; one cannot prove that the *only* relationship between the dependent variable and the instrument is through the effect of the instrument on the causal variable of interest (Cameron & Trivedi, 2009). While researchers can use theory and prior research to substantiate their instruments, economists have developed a handful of diagnostic statistics to test the exclusion assumption when there is more than one instrument for each endogenous regressor (i.e., an overidentified model)(Angrist & Pischke, 2008). There are also diagnostics to test other important aspects of IV specification and estimation such as the strength of the relationship between the instruments and the troublesome variable, regressor endogeneity, and the redundancy of multiple instruments. These test statistics can bolster the plausibility of the IVE model assumptions and can also indicate whether IVE is necessary. We implement and explain some of these diagnostics in the following sections.

Instrumental Variables Estimation

Selection of instrumental variables

To better understand state policy characteristics and to identify valid instruments for ECCE policy governance dispersion, we turned to a large literature in political science exploring the factors that influence a state's choice to adopt a given policy. In these studies, states are considered policy innovators (Walker, 1969), whose creation and adoption of policies is idiosyncratic (Gray, 1973), where internal influences combine with regional influences to affect the diffusion of policies to other states and further innovation (Berry & Berry, 1990; Mintrom, 1997). In their seminal paper, Berry and Berry (1990) defined the internal determinants of state policy adoption: state political, economic, and social characteristics. Political characteristics refer to both the political composition of elected officials and the political views of constituents. Economic characteristics refer to fiscal health, indicated by gross state product and unemployment as well as current levels of investment in a given policy. Social characteristics are variables like population, demographics, and personal income.

The determinants of state policy choices also vary across different policy areas (e.g., education or health) and policy tools (e.g., subsidies or regulations) (Fellowes & Rowe, 2004; Rigby, 2007; Soss, et al., 2001). With respect to child policy, there is some research on the determinants of state welfare policies in the post-PRWORA reform period. Corroborating the original work by Berry and Berry (1990), empirical research shows that public liberalism (Erikson, Wright, & McIver, 2003; Fellowes & Rowe, 2004; Ringquist, Hill, Leighley, & Hinton-Anderson, 1997), racism and racial diversity (Fellowes & Rowe, 2004; Hero & Tolbert, 1996; Rodgers, Beamer, & Payne, 2008; Soss, et al., 2001), party control (Fellowes & Rowe, 2004; M. A. Smith, 1997), government ideology and professionalism (Erikson, et al., 2003; Rodgers, et al., 2008), and state finances (Fellowes & Rowe, 2004; Tweedie, 1994) affect a state's level of generosity in their welfare policies. Overall, the less racist, more liberal and less class biased a state's constituency is, the more generous the welfare policies (Fellowes & Rowe, 2004; Rodgers, et al., 2008). Accordingly, Rigby (2007) controls for political ideology, party control, percentage of female legislators, wealth and economic conditions when examining the determinants of state ECCE policies. In particular, she finds that Democratic Party control and percentage of female legislators both predicted components of ECCE policy.

In addition to political partisanship, one can also measure how representatives in each state vote on children's issues. The Children's Defense Fund (CDF) documents state-level congressional voting records on child-related legislation whereby each state is scored by the percentage of 'pro-child' legislations (as determined by the CDF) for which the state's representatives voted (Children's Defense Fund, 2006). States also receive a ranking based on this legislative support (1-50). Both of these measures would be indicative of a state's child politics, and thus influence their governance structures.

The state-level characteristics used as instrumental variables are listed in Table 2.1 according to the Berry and Berry typology of states' political, social, and economic characteristics (1990). The political context variables are: percent women in the legislature, Democratic governor, and state ideology (index). Social characteristics are: percent population Hispanic, percent black, total population, and the number of children ages birth to five living in poverty. Economic characteristics are: gross state product, difference between state and federal minimum wage, maximum TANF benefit for a family per year, income per capita and the change in k-12 per-pupil expenditures for the five year period prior to the governance measure (2002-2007). We examined the 2005 values for all state-level variables in the kindergarten wave outcome analyses, and 2004 values for the outcomes measured at the 48-month wave. However, there was very limited variation in these variables within states over time, so we decided to use the levels in the pre-kindergarten year (2005) to 'represent' the states' characteristics. Pairwise correlations between the instrument set and the dispersion scale are available in Appendix C. These variables are all indicators of a state's policy context and are also correlated with dispersion of governance, but would only feasibly affect children's development through state policy. This is substantiated by the IVE diagnostic tests presented in the results section.

Data reduction of IVs using Principal Components Analysis

As discussed in the prior sections, there are myriad factors that can contribute to state decisions on policy governance. The central question here is "what causes differences between states in the dispersion of ECCE governance?" Yet without prior empirical evidence, the a priori selection of a single or a few variables to adequately instrument for governance is an inexact process. Therefore, it seemed intuitive to conceptualize this variation—the source of the endogeneity—as a latent omitted variable or a set of latent omitted variables. For example, the latent variables might be how much a state 'values' children or prioritizes child policy; alternatively, it could be the state's perspective on the role of government in the lives of young children. The state policy characteristics in the literature outlined above therefore served as indicators of this latent variable.

Principal Components Analysis (PCA) is a mathematical technique that reduces a set of variables into a smaller number of uncorrelated dimensions representing their core variation (Dunteman, 1989). These dimensions or components are linear weighted combinations of the original variables, where each consecutive component captures an additional dimension in the data (Vyas & Kumaranayake, 2006). Thus, PCA simply transforms the data without using a statistical model (Skrondal & Rabe-Hesketh, 2004).

PCA was useful for the present analyses for two reasons. First, it allowed the data to empirically determine the number of latent state factors as components. Secondly, it helped to reduce the number of state-level covariates that we identified as potential instruments to save model degrees of freedom. Though uncommon, the use of PCA to construct instrumental variables is useful for the latter purpose in systems or two-stage least squares estimations (Kloek & Mennes, 1960). We used varimax rotation to construct five orthogonal components using Stata's *pca* command, which became the instruments. We determined the number of components by the Kaiser-Guttman criterion, keeping the number of eigenvalues larger than one (Cattell, 1966). The factor loadings and the explained variance for each of the resulting five components are available in Appendix D & E. Note that we did not use PCA to develop substantive factors; we used it only to capture the primary variation in our set of state variables.

IVE isolates a specific portion of the covariation in the state-level variables and child outcomes, so the treatment effect generated from IVE is not the average treatment effect. The IV estimate represents the average causal effect for the subset of all states whose governance choices are responsive to the state context variables, known as the local average treatment effect (LATE)(Winship & Morgan, 1999). Assuming that these characteristics and their components would only affect child well-being vis-a-vis their influence on state's governance of ECCE policy in most states, using the resulting components as instruments would produce a valid LATE in IVE. We test this assumption in our results section below.

Model specification and estimation

We implemented IVE with Two-Stage Least Squares estimation using the *ivreg2* estimation package in Stata for all outcome analyses (Baum, Schaffer, & Stillman, 2010). All five components were included as instruments for both the continuous and dichotomous measures of governance.[12] We also used ivreg2 to generate diagnostic statistics that assess the strength, validity, and redundancy of IV estimates when the system is overidentified as mentioned above. We briefly describe these tests in IVE results section below.

We included the following control variables in all analyses: child sex (male), child race, low birthweight indicator, exposure to child care, age in months at time of assessment, indicator for mother's parity, mother's education (below HS, HS, some college, college+), mother's age, rural indicator, and an indicator for being in the top income quartile of the sample. The estimation routine includes these child- and family-level variables both in the first and second stage equations with the justification that if something is endogenous in the system, all of the system variables should be included in both stages even though they are not the identifying instruments (i.e., satisfying the exclusion restriction). This addresses the possibility that families can move or select into certain states for unobserved reasons and the idea that families 'vote with their feet', also known as a 'Tiebout effect' (Tiebout, 1956).

Modeling strategy

[12] As a check for robustness, we ran the same sets of IVE models that included the 'raw' state-level variables as instruments to compare the results with the PCA IVs. The PCA models proved to be more efficient, though there was no indication of serious inconsistency with the raw IVE method.

We estimated seven IVE models and eight OLS models that examine the effect of policy dispersion on kindergarten reading, math, and fine motor skills. Each consecutive IVE model estimates the effect of dispersion on a child-level outcome including an additional state-level covariate. We do this to ensure that the identified effect of dispersion is not explained by other important state policy characteristics, and to see the extent to which these factors may mediate the effects of governance on child skills. We indicate the relevant model numbers below as they appear in the results section.

Our base models (1, 8; IVE and OLS, respectively) include the child and family covariates listed in Table 1, which tests the overall effect of policy dispersion on child outcomes using our continuous dispersion measure. Next, we added region to the specification (2, 9) to capture price differences in the costs associated with ECCE policy implementation. The next models (3, 10) include an indicator for whether the state has a pre-k program. While it is also possible that pre-k is subject to the same endogeneity bias as governance, we wanted to insure that our governance and expenditure measures were not simply capturing a pre-k program effect. Lastly, we include our two measures of policy expenditures (4, 11), k-12 per-pupil expenditures and ECCE per-pupil expenditures, to detect whether policy spending changes the effect of dispersion. We also estimated an additional OLS model (12), representing a rich state-level covariate specification that includes each of the above state variables (region, pre-k, policy expenditures) along with the instrumental variables (components) as covariates to control for the internal determinants of state governance.

Our final specifications for estimating the effects of governance test for a non-linear effect of policy dispersion, whereby we replaced the scale measure of dispersion with our dichotomous indicator for highly dispersed (< 3). Our first models testing for the effects of highly dispersed governance (5, 13; IVE and OLS respectively) included region to capture price differences. We then added pre-k (6) to the IVE model only. Lastly, we estimated IVE and OLS models that include region, pre-k, and expenditures (7, 14). Again, we estimated an additional OLS model using the specification in model 14 along with the instrumental variables (components) to control for the internal determinants of state governance.

To test for the robustness of our estimates, we ran the same dispersion model specifications on reading at four years of age (excluding k-12 expenditures). These models include the same state variables in the PCA for instruments but with the 2004 values of each to represent the states' characteristics in the year prior to the ECLS-B children's fourth year of age (2005; kindergarten models use 2005 as the pre-kindergarten year). This resulted in four components instead of the five found for the kindergarten year.

Our modeling strategy includes a large number of models with several variables and significance tests using a single sample, increasing the likelihood of chance findings. We therefore tested for chance findings using the Benjamini-Hochberg adjustment to examine the probability that a given statistically significant relationship is a chance rejection of the null hypothesis (Benjamini & Hochberg, 1995). This adjustment indicated a low likelihood (< 10% chance) that any of our significant coefficients were due to chance.

Policy expenditures may also suffer from the same endogeneity as governance dispersion. Therefore, we estimated separate IVE models for all child outcomes that instrument for ECCE policy expenditures (combined CCDF and Head Start per-pupil spending) and omit dispersion to examine the extent to which the inclusion of governance mediated or moderated the influence of expenditures on policy outcomes in the dispersion models. We used the same set of components as instruments for expenditures and include all child and family covariates described above. For each outcome, we estimate a base model including only ECCE expenditures (1, 4, 7, 10; kindergarten reading, math, fine motor, and age-four reading, respectively). Following the modeling strategy for dispersion, we then add region to the estimation (2, 5, 8, 11), and then pre-k (3, 4, 9, 12).

Instrumenting for multiple endogenous variables

Including both governance and expenditures in one estimation may be problematic because both of these variables likely suffer from the same endogeneity. Since our IVE models are overidentified, we attempted to instrument for dispersion and ECCE expenditures simultaneously, but these models were not identified based on the IVE diagnostic statistics. This method is also generally ill-advised in some of the more recent econometrics literature (Angrist & Pischke, 2008). This same issue would apply to the indicator for state pre-k and k-12 expenditures. Therefore, we rely on our iterative modeling strategy outlined above to examine any consequential changes in direction, magnitude, and significance in the coefficient on policy dispersion to gauge the direction of bias.

Results

Instrumental Variable Diagnostics

We conducted five diagnostic procedures to test the strength of our IV specification and estimates: 1) F-statistic test of excluded instruments, which should be larger than 10 (Stock, Wright, & Yogo, 2002); 2) Lagrange Multiplier (LM) test of whether the excluded instruments are sufficiently correlated with the endogenous regressors (identification); 3) Hansen-J test of whether the instruments are valid (Baum, et al., 2010); 4) "Endogeneity test", defined as the difference of two Sargan-Hansen statistics indicating whether the endogenous regressor can be treated as exogenous (Baum, et al., 2010); 5) Bruesch-LM test for the redundancy of instruments (Breusch, Qian, Schmidt, & Wyhowski, 1999).

These statistics and their respective p-values[13] are reported at the bottom of each of the IVE model results in Tables 2.2-2.6. Our kindergarten outcome models satisfy the criteria for the tests above. The key assumption of IVE is that the instruments only affect the dependent variable through the endogenous variable of interest. The F-statistics and the Hansen-J tests support this assumption in almost all models; each of the F-statistic values were above 10, and we do not reject the Hansen-J null hypothesis that the instruments are validly excluded from the outcome equation. The only exceptions to the latter were in the math specifications using the dichotomous measure of dispersion (Table 2.3; 5, 6) and in the age-four reading models, but the F-statistics were above 10 in these models. With respect to the exclusion restriction, it appears as though the specifications that use the dispersion scale measure controlling for regional price differences and a state pre-k (models 2, 3) are the strongest models overall.

The LM test statistics were all sufficiently large such that we rejected the null hypothesis that the instruments were not sufficiently correlated with policy dispersion. It does appear that identification is weaker in models that include both dispersion and expenditures, and that the high dispersion models have smaller LM and F-statistics across all models. The some mixed results across models from the difference in the Sargan-Hansen statistics test in checking whether dispersion could be considered as exogenous, but the ambiguity in results suggests that IVE is appropriate. We also rejected the null hypothesis for

[13] The LM test p-values were 0.000 in all models and were excluded from the table; the LM statistic is reported.

all models that our instruments are redundant based on the Bruesch-LM test for redundancy. Overall the diagnostics indicate that our instruments are identified, valid, and non-redundant.

Dispersion of governance

The IVE and OLS outcome model results for kindergarten reading are displayed in Table 2.2, kindergarten math in Table 2.3, and kindergarten fine motor skills in Table 2.4. The results are displayed according to our modeling strategy outlined above with the model numbers indicated in parentheses. The metric for the coefficients is standard deviation (SD) unit change in child skill (as measured through IRT methods). Each model includes all the child and family covariates described in our modeling strategy but they are omitted from the results tables.

First, we tested our interval version of dispersion using the scale measure. Based on our strongest IVE models that control for regional price differences and pre-k (2, 3), the estimated effect of a one unit increase in dispersion was 0.11 on reading skills, 0.12 on math skills, and 0.06 on fine motor skills and were all statistically significant. This would imply that a one-unit increase in the dispersion scale is associated with a one-tenth of a SD increase in child reading and math skills at the beginning of their kindergarten year. As we move from model 1 through model 4 and add state-level covariates, the size and significance of the coefficient on dispersion is consistent for reading skills, but these covariates change the dispersion coefficient for math and fine motor skills. Including region and pre-k (2, 3) nearly doubles the dispersion scale coefficient for math (0.068 to 0.120) and it remains significant, and for fine motor the dispersion coefficient reaches significance and increases in magnitude (0.045 to 0.061) when these variables are included. The positive effect of dispersion also maintains its magnitude and significance for reading and math skills when accounting for policy expenditures (4), but not for fine motor skills. Neither ECCE nor k-12 per-pupil expenditures were significant in any of the kindergarten models.

We also tested whether the effect of dispersion was non-linear by including an indicator variable for highly dispersed governance, defined as being greater than three on the dispersion scale (5-7). The support for our IV estimates was not as strong for these specifications, but were still valid under some diagnostic criteria. Controlling for both region and pre-k (6; the specification that is analogous to our strongest model, 3, as described above), these models indicate that the effect of high dispersion of ECCE governance is 0.31 on kindergarten reading skills, and 0.32 on math skills. This means that children's reading skills are one-third of a SD higher in states with highly dispersed governance relative to states with more concentrated governance. The positive effect of high dispersion still holds when expenditures are included (7). There were no significant effects of high dispersion on kindergarten fine motor skills. As in the dispersion scale models, neither ECCE nor k-12 per-pupil expenditures were significant in the models using the highly dispersed variable.

For robustness, we examined the effect of governance on reading skills at the four-year wave (Table 2.5). The support for our IV estimates was not as strong for reading skills at four-years as they were for kindergarten. Based on the strongest IVE model specification for kindergarten reading that includes both region and pre-k (3), the estimated effect of a one unit increase in dispersion was 0.091 on reading skills at four-years of age. The coefficient remains significant but is reduced to 0.080 when we add ECCE policy expenditures to the specification (4). We did not find any significant nonlinear effects of dispersion in the models using the dichotomous indicator for high dispersion (5-7). However, the effect of ECCE per-pupil expenditures was significant with the dispersion scale measure (0.51), and also with the highly dispersed variable (0.62). This means that a one thousand dollar increase of state per-pupil expenditures in ECCE policy would increase children's reading skills at age-four by one-half of a standard deviation.

To compare our IVE results with OLS, we first look at the results in model 10 that includes both region and pre-k, akin to our strongest IVE specification (3). Based on this specification, the OLS estimated effect of dispersion is 0.22 on kindergarten reading skills, 0.23 on kindergarten math skills, and 0.25 on kindergarten fine motor skills; however, these coefficients were not significant. The coefficient on dispersion did not change appreciably in terms of magnitude, significance or direction as the state-level covariates and ECCE policy expenditures were added to the OLS specifications (8-11). The only exception to this is in the kindergarten reading base model (8), where the effect of dispersion on reading skills is 0.046 and then loses significance when region is added to the model (9), and decreases in size to 0.021. The direction of the dispersion coefficient switched from positive to negative for each kindergarten outcome when the IVs were included in the OLS specification (12; -0.019, -0.033, -0.0039 in reading, math, and fine motor, respectively), though none of these coefficients were significant. In the age-four reading models, dispersion was positive and significant with an effect of 0.039 controlling for region and pre-k (Table 2.5; 10) and remained significant when we added expenditures (11), but not when the IVs were included (12).

The OLS coefficients for highly dispersed were primarily negative and nonsignificant across all child outcomes and controlling for each state-level covariate (13-15). Highly dispersed becomes significant with an effect of -0.19 on kindergarten reading and math skills when the IVs are included as control variables (15). In the age-four reading models, the effect of highly dispersed is 0.026 with region and pre-k included (13), 0.044 with expenditures (14), and 0.013 with the IVs included (15), but the effect is never significant. These differences in direction, significance and magnitude are striking in contrast to the IV estimates which were positive and significant. In terms of efficiency, the standard errors of the IV estimates were slightly larger than in the OLS estimates (between one- and two-hundredths of a SD), which is expected because of the use of predicted values in the second-stage IVE equation.

Endogeneity bias

Comparing the magnitude of the coefficients between the OLS subject to state policy endogeneity and the assumingly unbiased IVE models indicates that the effect of dispersion is *downwardly biased* in OLS. This implies that the endogenous latent variables are either positively associated with dispersion and negatively associated with child skills, or negatively associated with dispersion and positively associated with child skills. However, because we have multiple instruments (five components) the IV estimates reflect the *net* reduction in bias from removing *the sum of these individual endogenous relationships*, each of which could be positive or negative. Because we do not know the true latent constructs represented by the components, we cannot determine the expected direction of the relationship between each construct, policy dispersion, and child skills. Therefore, we can only determine that state policy endogeneity imposes a negative *net* bias in the estimation of policy dispersion on child skills.

The other source of bias could be from the additional endogenous state-level control variables included in the dispersion models. Pre-k, ECCE per-pupil expenditures and k-12 per-pupil educational expenditures could all be related to a state's unobserved characteristics as well as child outcomes. Though instrumenting for all endogenous variables in the system was not feasible, an examination of the pattern of findings can help to understand this bias. The IVE coefficients for policy dispersion, which are purged of endogeneity, do not change drastically in terms of direction, significance or magnitude when these variables are added to the estimation with either dispersion variable (1-7). Some residual bias is certainly possible, but our dispersion results at least appear to be robust to this bias.

Expenditures

While understanding the role of governance in early childhood development was our primary goal, one cannot examine governance without considering expenditures. Because both of these state policy characteristics may suffer from endogeneity, we instrumented for ECCE per-pupil expenditures (excluding governance) to get an unbiased estimate of their effect on kindergarten outcomes and age-four reading skills. We present three model specifications for each of the four outcome variables in Table 2.6 as described in the modeling strategy. These estimates revealed some positive effects of expenditures for reading and math, but not for fine motor skills. A one thousand dollar increase in ECCE per-pupil expenditures is associated with a 1.21 SD increase in kindergarten math skills, and 1.15 SD when the indicator for pre-k was included (6). The coefficient was slightly smaller for reading skills, 1.01 SD (2), but it was not significant when pre-k was included (3).

Because neither the ECCE nor k-12 educational expenditures were significant in the dispersion models for kindergarten outcomes, our results may indicate that governance mediates the effect of expenditures on child skills. We did find that the effect of expenditures on reading skills at age-four was stronger than in kindergarten—up to eight-tenths of a SD larger. The larger effects at four years may be because the impact of ECCE expenditures on children's learning would be more direct (for those children exposed to the ECCE system) during the preschool-aged measurement than their more distal effects later on in kindergarten. This is also consistent with the positive significant coefficient on state pre-k in the age-four reading specifications instrumenting for policy dispersion (Table 2.5; 3, 4).

Discussion

This study was a test of whether more concentrated or more dispersed approaches to state governance affect the performance of agencies in accomplishing policy goals. Early child care and education was a perfect field to test this question because of the nationwide differences in the state governance of these policies. There are many theoretical and practical arguments describing why governance over children's policies matters, and include explanations that strongly favor concentrated approaches in terms of the impacts on children's well-being, and others that strongly favor dispersed approaches in terms of producing beneficial outcomes. States have even made dramatic changes to their governance structures in response to theories about the benefits of vertical ECCE policy governance; in the past five years, Massachusetts, Pennsylvania and Georgia consolidated all child-related and ECCE programs together into one state agency created expressly for child policy. Yet the extent to which governance affects individual outcomes has been under-investigated and, until this study unknown. Therefore, our analyses were motivated by these unresolved but strongly held theories about whether one of these approaches to governance actually results in children being better off, and whether it is worthwhile to change the design of state governance.

There are three primary contributions of this paper. We provide the first empirical investigation of the effect of state-level ECCE governance on early childhood well-being. We add to the body of work in public management by measuring and examining a dimension of horizontal governance—policy dispersion—and looking at its effect on policy goals. We also use a theoretically unbiased and well-implemented approach to address the endogeneity of state policy by developing instrumental variables for state policy governance with principal components and rich state-level data. We use the IVE approach with a large and nationally representative sample of young children to produce unbiased estimates of the effect of policy dispersion on children's reading, math, and fine motor skills at age five.

We find that more horizontally dispersed governance in state ECCE policy is associated with policy-significant improvements in child reading and math skills in kindergarten. In our strongest model (based on the IVE diagnostic statistics), we find that a one-unit increase in the scale measure of dispersion is associated with an approximately one-tenth of a standard deviation increase in both child reading and math skills at the beginning of their kindergarten year, as well as a 0.06 SD increase in fine motor skills. This effect was robust to different model specifications that account for regional price differences, state pre-kindergarten programs, and both ECCE and k-12 per-pupil expenditures. The positive effect of dispersion was also robust to estimating reading skills at age four, with an effect of 0.091 SD. Our OLS estimates suggest that not accounting for the endogeneity of state unobserved characteristics would downwardly bias or underestimate the effect of dispersion.

We also tested for a non-linear effect of policy dispersion using a dichotomous indicator for states with highly dispersed governance (i.e. greater than three on the dispersion scale). Our results show that children's kindergarten reading and math skills are one-third of a SD higher in states with highly dispersed governance relative to states with more concentrated governance, though our dispersion scale model results were the strongest in terms of support from the IVE diagnostics. We did not find any significant effects of high dispersion at the age-four wave, but the diagnostic statistics for these models did not as strongly support the central assumption of IVE (i.e. instruments are validly excluded from the outcome equation). This difference in effects and identification may be an issue of exposure. While many children would have had some exposure to the state's ECCE governance via a pre-k or a child care program by the kindergarten measurement, it is less likely that children would necessarily have substantial exposure to ECCE policy at precisely 48 months of age at the ECLS-B assessment. The ECLS-B is a representative sample of children born in 2001 and not a representative sample of children in ECCE programs.

The dominant hypothesis from the child development literature was that dispersion or fragmentation was detrimental to children's well-being (Gallagher, et al., 2004; Kagan & Kauerz, 2012; Kamerman & Kahn, 2001; Pianta, et al., 2009). For this reason, the most interesting part of this study was that our policy effect was in the opposite direction of the dominant hypothesis; fragmentation of child policy—to the extent that this is measured by policy dispersion—was not detrimental to child well-being. Indeed, dispersion appears to be beneficial for children's skill development in early childhood. This finding is consistent with the research on consolidated or integrated delivery of children's mental health services reviewed earlier. Earlier studies in this field found that system-level change cannot affect child outcomes unless, "children receive services that they would not have received had there not been a change at the system level" (Bickman, 1996, p. 697). In states that have more centralized or managed-care like governance, children could have ended up receiving lower-quality care because implementing an integrated approach is challenging (Rivard & Morrissey, 2003) and more resources may go into coordination to the detriment of improving the effectiveness of services. Finding that outcomes were worse in a less dispersed state could imply that consolidating governance would not necessarily improve actual services, and may also mean that policy activities and services that are administered individual agencies with more targeted, specific missions are implemented and delivered more effectively.

Our conceptualization of policy dispersion was akin to Kettl's dimensions of vertical and horizontal governance, and these ideas can help to explain our findings. With more horizontal governance and thus greater dispersion of policies across agencies, the control over workaday policy decisions may be more spread out. This could mean that agency administrators and front-line staff have more professional discretion in serving clients, allowing them to match clients with programs more effectively. In turn, the more consolidated, hierarchical, vertically-controlled governance approach could inhibit agency activity because staff are less autonomous and are more restricted with respect to using their professional discretion (Moe, 1984). As the number of agencies within a policy field increases, this could also cultivate competitive forces between agencies that incentivize better performance and improve the quality of direct services (Chubb & Moe, 1988). In addition, agencies within horizontal designs may have more focused missions for which they are held accountable, and may be more aware of relevant indicators of policy and job performance.

These concepts also relate to our results for policy spending. Though understanding the role of expenditures in ECCE policy was not our primary goal, we found evidence to suggest that policy expenditures may affect child outcomes through their effects on governance. It may be that vertical or consolidated agencies are excessively top-heavy with resources going disproportionately towards the 'rents' of high-level managers instead of going towards direct service. In comparison, the horizontal arrangements may be 'leaner' with fewer top-level bureaucrats with more of a focus on direct services and benefits for clients.

Alternatively, the command and control techniques of vertical governance may be less effective at policy implementation than the interagency collaboration techniques of more horizontally structured approaches (Jennings, 1994; Provan & Milward, 2001). It may be that one of the mechanisms within the 'black box' of policy dispersion is a classic issue in policy and public management—coordination (North, 1990; Pollitt & Bouckaert, 2011). Our results may suggest that vertical approaches to ECCE governance do not necessarily have effective *coordination* between programs (Jennings & Ewalt, 1998; Lynn, et al., 2001; Martinson, 1999; Pollitt & Bouckaert, 2011). Intergovernmental collaboration research indicates that coordination was the specific mechanism that improves organizational and policy performance in large part because it minimizes the burden for families of dealing with multiple agencies (Adams, et al., 2002; Jennings, 1994; Jennings & Ewalt, 1998). Truly integrated or consolidated governance would need to somehow reduce costs, make fewer demands on clients, and ultimately help families and children receive the services they need (Jennings, 1994; Martinson, 1999). Therefore, states would have to go further than just co-locating or consolidating services into an agency to affect child-level outcomes; they must *coordinate* them so parents do not have to wait for long periods between appointments and cultivate a more client-oriented culture (Adams, et al., 2002; Nowell, 2009). In other words consolidation is not a silver bullet, and co-located does not mean *co*ordinated (Ling, 2002).

So why would states with more dispersed governance have better coordination? Autonomous agencies may have more *incentive* to coordinate in a horizontally dispersed system, and therefore more dispersed states have developed better coordination strategies (Bardach, 1998). For one, organizations in the ECCE policy field may have a particularly strong financial incentive to collaborate. This is because ECCE finance is complicated and often involves blending or 'braiding' of funding streams, each with its own requirements and eligibility criteria (e.g. when a child uses both subsidized child care and state pre-k)(Barnett, et al., 2009; Grubb & McDonnell, 1996; Hustedt & Barnett, 2011; Schultz, 2009).

Scholars from several traditions such as organizational, resource dependence and exchange, bureaucratic-administrative, and contingency theorists look at organizational incentives, capacity, and connectedness to understand successful interagency collaboration (Meyers, 1993). There may be a 'functional' incentive for ECCE agencies to collaborate because it could improve program outcomes (Weiss, 1987). This may imply that in multiple-agency governance there are smooth functioning, established divisions of labor which allow agencies to coordinate more successfully while still maintaining their own autonomy and legitimacy (Grubb & McDonnell, 1996). Furthermore, the idea of reciprocal interdependence, and similarly, adaptive efficiency, suggest that organizations develop a specialized function and then *rely* on this network of continuing interaction to achieve their goals, with the operations of each organization creating contingencies for other actors in the network (North, 1990; O'Toole & Montjoy, 1984). It could also be that states with better inter-organizational information technology have coordinated data systems and are better able to overcome institutional boundaries as a result (Gruendel & Stedron, 2012).

Relatedly, case management likely plays a role in the causal chain between policy governance and individual-level outcomes. The seminal work of Lipsky highlights the importance of front-line staff or 'street-level bureaucrats' who ultimately define policy in social agencies because they determine the services that are delivered by the government (1980). Caseworkers are the street-level bureaucrats that coordinate child services across sectors (Vinson, et al., 2001). In this way, more dispersed systems may have more or better caseworkers and provide them with greater discretion to find more effective services which enable better client-to-policy interactions, increasing child access to higher quality and, apparently more effective programs. In states where programs are concentrated under fewer roofs, a child's caseworker may not necessarily be knowledgeable about every program under that roof, but still act as the 'gatekeeper' to government programs thereby reducing policy access. In addition, the discretion of the caseworker may be more restricted by rules and "red tape" thereby increasing the transaction costs of finding and gaining access to the most effective package of services. Furthermore, adding new responsibilities to caseworkers through consolidation without specific preparation or training for staff would not help integrate services and could also contribute to staff frustration (Meyers, 1993). Still, parents may interact with numerous caseworkers even if ECCE services were consolidated into one agency—one caseworker could do eligibility, one could coordinate child care, another for pre-k, etc. Agencies control factors related to caseworker-client interactions such as total responsibilities of caseworkers, caseloads, staff turnover rates, and access to appropriate technology which all affect how well caseworkers can link families to services (Adams, et al., 2002; Sandfort, 1999). These factors are all potential mechanisms through which dispersion and governance may affect child development, and should be explored in future work.

Future research

To continue the investigation of policy governance and build the causal evidence, it will be important to collect time-varying measures of governance and policy dispersion and test the competing hypotheses we outlined here using state fixed effects. A pre-post examination of states that have transitioned from low to high or high to low dispersion would also be informative. We used the ECCE policy field to investigate the effects of governance on policy outcomes, but these analyses should be replicated in other policy fields such as health care and with the spectrum of welfare policies. With respect to measurement and construct validity, developing a more refined measure would help us to understand the dynamics of dispersion, since there are likely to be diminishing returns to increasing dispersion.

While our study detected an overall effect of policy dispersion, future work should investigate the more specific mechanisms through which governance translates to child outcomes, or is mediated or moderated by other factors in the policy environment. For example, our results indicated that expenditures were significant on their own but were not when we included governance. This may suggest that it is not necessarily how much money states spend, but whether funds are allocated efficiently through the governance structures. Furthermore, there are a number of ECCE agency characteristics and aspects of the front-line conditions like case-management that are likely important components of the governance-to-policy outcome logic model. Exploring the role of interagency coordination is also worthwhile. Prior research indicates that governments can facilitate coordination by: holding regular meetings of staff across different units and cultivating good interdepartmental relations, using an electronic client service system and consolidated application forms, appointing interdepartmental liaisons, providing strong leadership, and establishing consistent and well-identified referral mechanisms (Bardach, 1998; Grubb & McDonnell, 1996; Hodges, Hernandez, & Nesman, 2003; Jennings, 1994; Nowell, 2009; Pollitt, 2003; Rivard & Morrissey, 2003; Vinson, et al., 2001). Collecting data on these types of characteristics and including them in analyses will help to uncover some of the mechanisms along the causal path between governance and child outcomes. Including more information about statewide data systems will also become increasingly important for research as states improve their information technology competence and attempt to use more big-data for policy problem-solving (Dunleavy & Margetts, 2010).

Limitations

We present the diagnostic statistics of our IV estimates to justify their validity, but these tools are not foolproof. Our method should be replicated and improved by collecting more state-level characteristics and with state fixed effects with a time-varying measure of governance. Bias from expenditures or pre-k is still possible, but our robustness test results suggest that the governance estimate is valid. Finally, our measures of governance with the policy dispersion scale may be overly simplistic, but we consider the measurement contribution of our paper as exploratory.

TABLE 2.1: VARIABLE NAMES, DESCRIPTIVE STATISTICS, AND DATA SOURCE BY VARIABLE TYPE

Variable type	Variable name	Mean	SD	Data Source
	State ECE Policy			
Governance	Dispersion scale (1-5)	2.5	1.1	NCCIC
	Highly-dispersed (Dispersion scale >3; %)	14.9		NCCIC
Policy investment	Combined Head Start and CCDF per-pupil expenditur	0.31	0.069	NCCP & NIEER
Policy development	State has pre-kindergarten program (%)	90.1		NIEER
	State characteristics*			
Economic				
Fiscal health	Gross State Product (millions)	######	508371.7	BEA
	Income per capita (thousands)	34.3	4.7	BEA
Policy investment	Changes in K-12 per-pupil expenditures 2002-2007 (t	1.7	0.79	NCES
Social				
	Population size (thousands)	12171.8	11060.0	US Census
Poverty	Number of children ages 0-5 in poverty (thousands)	178.0	174.5	US Census
Racial/Ethnic	Percent population Hispanic	12.5	10.9	US Census
	Percent population black	11.3	7.9	US Census
Policy generosity	Difference between federal and state minimum wage	0.52	0.76	BLS
	Maximum TANF benefit for family/year	4965.0	1998.5	
Political				
Elected officials	State Government Ideology Index ranking (+ more	45.7	27.0	ICPSR
	Percent women in legislature	22.5	6.6	CAWP
Party control	Governor is democrat (%)	49.3		CSG
Child politics	CDF Congressional scorecard ranking	25.0	12.1	CDF
	CDF Congressional scorecard percentage (+better)	41.9	21.5	CDF
	Child and family-level characteristics**			
Child				
	Child is male (%)	51.0		
	Child age at assessment (months)	68.1	4.4	
	Child was born low birth weight (%)	7.4		
	Ethnicity (%)			
	White	54.0		
	Black	14.3		
	Hispanic	24.5		ECLS-B
	Asian	2.5		
	Other	4.5		
	Attends child care (%)	40.3		
	Reading skills (IRT Theta score)	0.13	0.92	
Child outcomes	Math skills (IRT Theta score)	0.16	0.90	
	Fine motor skills (IRT Theta score)	0.16	0.92	
Family				
	Mother's age at child's birth	28.3	6.37	
	Primary caregiver's highest education level (%)			
	Below High School	14.8		
	High School degree or equivalent	27.0		
	Some college	30.8		ECLS-B
	College degree or higher	27.5		
	Family in highest income quartile (%)	30.4		
	Mother multiparous (%)	64.3		
	South (region; %)	36.8		
	Rural (%)	16.2		

[*] All values of state variables are for 2005 unless otherwise stated

[**] Characteristics of children in kindergarten wave (n=6700); weighted

Data source key	
Interuniversity Consortium for Political and Social Research	ICPSR
National Institute for Early Education Research, Rutgers University	NIEER
National Center for Children in Poverty, Columbia University	NCCP
National Center for Education Statistics, Institute for Education Sciences, Dept. of Education	NCES
National Child Care Information and Technical Assistance Center, Administration for Children and Families	NCCIC
The Council for State Governments	CSG
Center for American Women in Politics	CAWP
Bureau of Economic Analysis, Dept. of Commerce	BEA
Children's Defense Fund	CDF
Bureau of Labor Statistics	BLS
Early Childhood Longitudinal Study - Birth Cohort (NCES)	ECLS-B

Note: Several state variables were consolidated into one dataset by the University of Kentucky Center for Poverty Research (UKCPR)

TABLE 2.2: INSTRUMENTAL VARIABLES ESTIMATION AND OLS RESULTS FOR THE EFFECT OF POLICY GOVERNANCE ON KINDERGARTEN READING SKILLS

	Dispersion IVE Models							Dispersion OLS Models							
	Base model	With region	With pre-k	With expend.	High disp. (0-1)	High disp. with pre-k	High disp. with expend	Base Model	With region	With pre-k	With expend.	With all IVs	High disp. (0-1)	High disp. with expend	High disp. with all IVs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Dispersion of Governance (1-5)	0.11	0.11	0.11	0.086				0.046	0.021	0.022	0.024	-0.019			
	(0.029)*	(0.030)*	(0.031)*	(0.031)*				(0.019)*	(0.019)	(0.019)	(0.021)	(0.032)			
South		0.015	0.00016	0.017	0.050	0.017	0.033		0.12	0.12	0.11	0.11	0.17	0.17	0.17
		(0.052)	(0.054)	(0.062)	(0.061)	(0.068)	(0.067)		(0.050)*	(0.052)*	(0.060)	(0.12)	(0.052)*	(0.055)*	(0.094)
Pre-k program			0.088	0.081		0.14	0.13			0.045	0.045	0.047	0.014	0.014	-0.0026
			(0.063)	(0.069)		(0.082)	(0.085)			(0.062)	(0.069)	(0.084)	(0.064)	(0.066)	(0.081)
ECCE per-pupil expenditures (K)				0.17			0.21				0.11	-0.38		0.066	-0.47
				(0.28)			(0.29)				(0.27)	(0.30)		(0.28)	(0.29)
K-12 per-pupil expenditures (K)				-0.011			0.0075				-0.0039	-0.051		-0.0028	-0.053
				(0.0081)			(0.0094)				(0.0080)	(0.028)		(0.0081)	(0.024)*
Highly dispersed (>3)					0.27	0.31	0.33						-0.060	-0.062	-0.19
					(0.11)*	(0.11)*	(0.13)*						(0.067)	(0.071)	(0.084)*
Observations^	6700	6700	6700	6700	6700	6700	6700	6700	6700	6700	6700	6700	6700	6700	6700

Instrumental Variable Diagnostics							
F	30.8	38.0	37.0	37.8	15.7	15.1	15.8
LM stat	61.4	44.8	46.5	46.7	30.4	31.6	30.8
Hansen J	1.65	2.24	1.11	9.22	8.80	7.34	8.09
pval	0.80	0.69	0.89	0.056	0.066	0.12	0.088
Sargan-Hansen	8.45	11.2	11.9	6.90	9.98	11.4	12.9
pval	0.0037	0.00081	0.00055	0.0086	0.0016	0.00075	0.00033
Bruesh LM	40.4	46.9	52.0	50.1	26.5	31.1	34.1
pval	0.000000	1.6e-09	1.4e-10	3.4e-10	0.000026	0.000002	0.00000070

* p<0.05; Standard errors in parentheses; ^ Observations rounded to the nearest 50 per ECLS-B security requirements

TABLE 2.3: INSTRUMENTAL VARIABLES ESTIMATION AND OLS RESULTS FOR THE EFFECT OF POLICY DISPERSION ON KINDERGARTEN MATH SKILLS

	Dispersion IVE Models							Dispersion OLS Models							
	Base model	With region	With pre-k	With expend.	High disp. (0-1)	High disp. with pre-k	High disp. with expend	Base Model	With region	With pre-k	With expend.	With all IVs	High disp. (0-1)	High disp. with expend	High disp. with all IVs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Dispersion of	0.068	0.12	0.12	0.10				0.016	0.020	0.023	0.021	-0.033			
Governance (1-5)	(0.029)*	(0.030)*	(0.030)*	(0.031)*				(0.018)	(0.017)	(0.018)	(0.018)	(0.027)			
South		-0.14	-0.16	-0.14	-0.096	-0.13	-0.12		-0.019	-0.031	-0.019	0.032	0.021	0.030	0.068
		(0.048)*	(0.050)*	(0.062)*	(0.060)	(0.065)*	(0.067)		(0.040)	(0.041)	(0.049)	(0.087)	(0.044)	(0.046)	(0.078)
Pre-k program			0.13	0.12		0.18	0.17			0.078	0.070	0.063	0.049	0.044	0.021
			(0.082)	(0.085)		(0.095)	(0.099)			(0.079)	(0.080)	(0.087)	(0.080)	(0.079)	(0.087)
ECCE per-pupil				0.12			0.16				0.039	-0.45		-0.00005	-0.51
expenditures (K)				(0.27)			(0.28)				(0.26)	(0.28)		(0.26)	(0.27)
K-12 per-pupil				-0.0048			0.017				0.0042	-0.025		0.0053	-0.030
expenditures (K)				(0.0089)			(0.0092)				(0.0082)	(0.027)		(0.0080)	(0.025)
Highly dispersed (>3)					0.27	0.32	0.39						-0.053	-0.048	-0.19
					(0.11)*	(0.12)*	(0.13)*						(0.065)	(0.067)	(0.074)*
Observations^	6700	6700	6700	6700	6700	6700	6700	6700	6700	6700	6700	6700	6700	6700	6700

Instrumental Variable Diagnostics							
F	30.7	37.8	36.8	37.5	15.6	15.0	15.7
LM stat	61.3	44.8	46.5	46.7	30.4	31.5	30.8
Hansen J	12.4	3.62	2.66	6.57	12.1	10.5	6.16
pval	0.015	0.46	0.62	0.16	0.017	0.033	0.19
Sargan-Hansen	4.73	13.4	14.0	8.91	9.53	11.2	14.2
pval	0.030	0.00025	0.00018	0.0028	0.0020	0.00083	0.00017
Bruesh LM	40.4	46.9	52.0	50.1	26.4	31.1	34.1
pval	0.000000	1.6e-09	1.4e-10	3.4e-10	0.00002	0.00000	0.00000071

* p<0.05; Standard errors in parentheses; ^ Observations rounded to the nearest 50 per ECLS-B security requirements

TABLE 2.4: INSTRUMENTAL VARIABLES ESTIMATION AND OLS RESULTS FOR THE EFFECT OF POLICY DISPERSION ON KINDERGARTEN FINE MOTOR SKILLS

	Dispersion IVE Models							Dispersion OLS Models							
	Base model	With region	With pre-k	With expend.	High disp. (0-1)	High disp. with pre-k	High disp. with expend	Base Model	With region	With pre-k	With expend.	With all IVs	High disp. (0-1)	High disp. with expend	High disp. with all IVs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Dispersion of Governance (1-5)	0.045 (0.027)	0.063 (0.031)*	0.061 (0.031)*	0.056 (0.030)				0.022 (0.015)	0.027 (0.017)	0.025 (0.017)	0.021 (0.018)	-0.0039 (0.024)			
South		-0.071 (0.056)	-0.063 (0.058)	-0.065 (0.063)	-0.050 (0.057)	-0.044 (0.063)	-0.055 (0.061)		-0.027 (0.045)	-0.017 (0.047)	-0.012 (0.051)	-0.013 (0.087)	0.022 (0.045)	0.025 (0.046)	0.027 (0.082)
Pre-k program			-0.048 (0.070)	-0.035 (0.073)		-0.029 (0.083)	-0.0051 (0.082)			-0.065 (0.062)	-0.055 (0.063)	-0.069 (0.068)	-0.082 (0.064)	-0.071 (0.064)	-0.096 (0.071)
ECCE per-pupil expenditures (K)				-0.43 (0.25)			-0.40 (0.25)				-0.46 (0.25)	-0.68 (0.27)*		-0.49 (0.25)*	-0.74 (0.27)*
K-12 per-pupil expenditures (K)				0.0027 (0.0097)			0.015 (0.0094)				0.0067 (0.0093)	-0.0063 (0.023)		0.0086 (0.0091)	-0.0055 (0.021)
Highly dispersed (>3)					0.15 (0.12)	0.14 (0.12)	0.22 (0.12)						-0.017 (0.046)	-0.018 (0.048)	-0.095 (0.055)
Observations^	6600	6600	6600	6600	6600	6600	6600	6600	6600	6600	6600	6600	6600	6600	6600

Instrumental Variable Diagnostics							
F	31.4	38.4	37.4	38.1	15.5	14.9	15.8
LM stat	61.7	45.0	46.6	47.2	30.8	31.9	31.2
Hansen J	2.81	2.02	1.90	3.38	3.40	3.36	3.33
pval	0.59	0.73	0.75	0.50	0.49	0.50	0.50
Sargan-Hansen	1.62	2.05	2.31	3.20	2.70	3.21	5.93
pval	0.20	0.15	0.13	0.074	0.10	0.073	0.015
Bruesh LM	40.9	47.2	52.0	50.4	26.9	31.3	34.3
pval	0.00000(	1.4e-09	1.4e-10	3.0e-10	0.00002	0.00000	0.00000063

* p<0.05; Standard errors in parentheses; ^ Observations rounded to the nearest 50 per ECLS-B security requirements

TABLE 2.5: INSTRUMENTAL VARIABLES ESTIMATION AND OLS RESULTS FOR THE EFFECTS OF POLICY DISPERSION ON AGE-FOUR (PRESCHOOL) READING SKILLS

	Dispersion IVE Models							Dispersion OLS Models							
	Base model	With region	With pre-k	With expend.	High disp. (0-1)	High disp. with pre-k	High disp. with expend	Base Model	With region	With pre-k	With expend.	With all IVs	High disp. (0-1)	High disp. with expend	High disp. with all IVs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Dispersion of Governance (1-5)	0.031	0.056	0.091	0.080				0.023	0.025	0.039	0.037	0.018			
	(0.019)	(0.029)*	(0.029)*	(0.028)*				(0.014)	(0.015)	(0.015)*	(0.014)*	(0.019)			
South		-0.050	-0.083	-0.053	0.053	-0.0013	-0.0060		-0.010	-0.021	-0.0013	0.047	0.016	0.029	0.056
		(0.051)	(0.048)	(0.048)	(0.051)	(0.054)	(0.053)		(0.035)	(0.036)	(0.035)	(0.047)	(0.036)	(0.034)	(0.048)
Pre-k program			0.16	0.14		0.11	0.13			0.11	0.096	0.040	0.085	0.080	0.029
			(0.052)*	(0.051)*		(0.069)	(0.068)			(0.032)*	(0.036)*	(0.039)	(0.037)*	(0.038)*	(0.041)
ECCE per-pupil expenditures (K)				0.51			0.62				0.53	0.0068		0.57	-0.019
				(0.22)*			(0.21)*				(0.22)*	(0.26)		(0.23)*	(0.27)
Highly dispersed (>3)					-0.086	0.075	0.15						0.026	0.044	0.013
					(0.098)	(0.12)	(0.11)						(0.052)	(0.054)	(0.063)
Observations^	8300	8300	8300	8300	8300	8300	8300	8300	8300	8300	8300	8300	8300	8300	8300

Instrumental Variable Diagnostics							
F	27.9	24.2	24.8	18.0	15.6	12.2	12.5
LM stat	52.7	31.2	32.7	31.1	27.5	25.1	23.8
Hansen J	18.3	15.4	13.3	13.1	21.5	19.2	19.5
pval	0.00039	0.0015	0.0040	0.0045	0.000083	0.00025	0.00022
Sargan-Hansen	0.0020	1.01	3.61	3.01	0.23	0.20	0.42
pval	0.96	0.32	0.057	0.083	0.63	0.65	0.52
Bruesh LM	21.3	25.3	35.0	28.3	22.4	20.9	20.0
pval	0.000089	0.000014	0.000000	0.000003	0.000053	0.00011	0.00017

* p<0.05; Standard errors in parentheses; ^ Observations rounded to the nearest 50 per ECLS-B security requirements

TABLE 2.6: INSTRUMENTAL VARIABLES ESTIMATION RESULTS FOR THE EFFECT OF POLICY EXPENDITURES ON KINDERGARTEN READING, MATH, FINE MOTOR, AND AGE-FOUR READING SKILLS

	Kindergarten Reading			Kindergarten Math			Kindergarten Fine Motor			Age-four Reading		
	Base model	With region	With pre-k	Base model	With region	With pre-k	Base model	With region	With pre-k	Base model	With region	With pre-k
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ECCE per-pupil expenditures (K)	0.33	1.01	1.03	1.07	1.21	1.15	-0.080	-0.050	0.19	1.53	1.82	1.76
	(0.48)	(0.51)*	(0.56)	(0.46)*	(0.52)*	(0.51)*	(0.48)	(0.49)	(0.51)	(0.31)*	(0.32)*	(0.34)*
South		0.18	0.18		0.039	0.035		0.0058	0.021		0.083	0.083
		(0.049)*	(0.053)*		(0.049)	(0.051)		(0.042)	(0.043)		(0.037)*	(0.038)*
Pre-k program			-0.0086			0.019			-0.085			0.031
			(0.079)			(0.093)			(0.075)			(0.049)
Observations^	6700	6700	6700	6700	6700	6700	6600	6600	6600	8300	8300	8300
Instrumental Variable Diagnostics												
F	21.2	17.1	18.9	21.2	17.2	19.0	22.2	17.8	19.2	29.8	29.2	35.5
LM stat	45.7	37.6	63.3	45.7	37.6	63.4	46.5	38.5	64.7	43.8	41.7	55.3
Hansen J	12.5	9.00	8.80	9.94	10.9	11.4	5.42	5.40	4.81	5.24	1.50	1.74
pval	0.014	0.061	0.066	0.041	0.027	0.022	0.25	0.25	0.31	0.15	0.68	0.63
Sargan-Hansen	1.05	3.17	3.25	3.81	2.65	2.41	1.43	1.43	2.27	15.5	20.0	17.6
pval	0.30	0.075	0.072	0.051	0.10	0.12	0.23	0.23	0.13	0.000085	0.000007	0.000027
Bruesh LM		34.3	45.3	33.8	34.3	45.3	34.3	34.9	45.7	34.7	41.4	51.4
pval		0.000000	3.4e-09	0.000000	0.000000	3.4e-09	0.000000	0.000000	2.8e-09	0.000000	5.4e-09	4.1e-11

* $p<0.05$; Standard errors in parentheses; ^ Observations rounded to the nearest 50 per ECLS-B security requirements

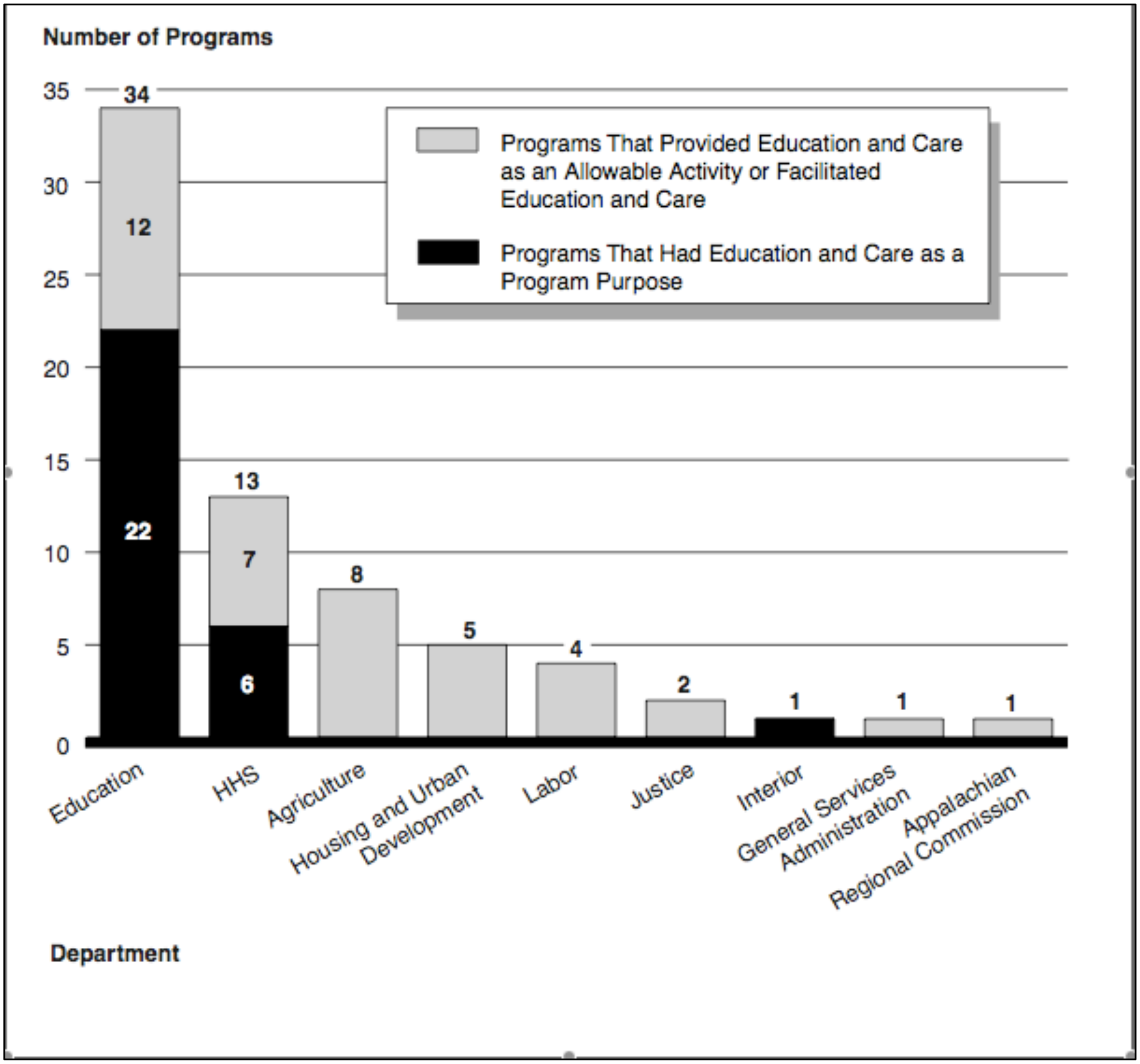


FIGURE 2.1: NUMBER OF FEDERAL PROGRAMS THAT PROVIDE OR SUPPORT EDUCATION AND CARE FOR CHILDREN UNDER AGE 5, BY DEPARTMENT OR AGENCY

Source: General Accounting Office (2000) Early Education and Care: Overlap Indicates Need to Assess Crosscutting Programs. Washington, DC: U.S. Government Printing Office.

CHAPTER 3. PARENTING SKILLS AND EARLY CHILDHOOD DEVELOPMENT: PRODUCTION FUNCTION ESTIMATES FROM LONGITUDINAL DATA

Introduction

Cognitive achievement in early childhood is strongly associated with a range of welfare outcomes in later life. In the U.S., test scores as early as 2 years of age are associated with later educational attainment as well as adult wages (Case & Paxson, 2006; Feinstein, 2003). In poor countries, early (by age 5) cognition and social-emotional development are strong determinants of school enrollment and achievement scores in adolescence, grade repetition, and overall grade attainment (Grantham-McGregor et al., 2007). Moreover, a related literature establishes that the *gap* in cognitive achievement between children of low and high socioeconomic status appears very early in life (Bradley & Corwyn, 2002; G. J. Duncan & Brooks-Gunn, 1997; G. J. Duncan, et al., 1998; Grissmer & Eiseman, 2008), prior to school-entry and even as early as age one (Carneiro, Heckman, & Masterov, 2005). This pattern in the achievement gap is also documented for a developing country in Paxson & Schady (2007).

Research from neurobiology, development psychology, and physiology provide ample explanation for the strong relationship between development by age 5 and later life outcomes. At birth, the brain is dependent upon interactions, experiences, and environmental stimulation for healthy development, which affect everything from molecules to neurological systems (Als, et al., 2004; Dawson, et al., 2000; Greenough, et al., 1987; Lupien, et al., 2000; McEwen, 2001). Early childhood is considered a 'sensitive period' because the brain overproduces synapses during the first two years of life and thus the brain's circuitry is extremely responsive to experiences during this period (Fox, et al., 2010; Hess, 1973; Knudsen, 2004; Levitt, 2008; Singer, 1995; Trachtenberg & Stryker, 2001). Furthermore, prolonged stress (due to familial chaos or emotional or physical abuse) in early childhood increases growth threatening hormones and disrupts appropriate brain development which in turn leads to greater susceptibility to mental health problems and stress-related physical illnesses (NSCDC, 2007). Indeed 85 percent of the brain's core structure is formed by age three; thus, experience-based brain development that occurs very early (prior to school-entry) sets pathways for future learning and growth that affect skills and well-being for life. For these reasons, researchers are often concerned with children's *readiness* for school and examine child cognitive outcomes at preschool and kindergarten as indicators of success and well-being in later childhood and young adulthood (Brooks-Gunn & Markman, 2005; Claessens, Duncan, & Engel, 2009; G. J. Duncan, et al., 2007; Raver, Gershoff, & Aber, 2007; Rouse, Brooks-Gunn, & McLanahan, 2005).

Despite the known importance of the early childhood life experience for school readiness and future success, there is a dearth of population–level evidence on the exact familial inputs that are important for a child's early cognitive development. Most of the published work in economics and public policy estimates the education production function (EPF) on data from school-aged children and focuses on school inputs such as class size (Angrist & Lavy, 1999), peer effects, and teacher characteristics (Angrist & Lavy, 1999; Hanushek, 1992; Hanushek, Kain, Markman, & Rivkin, 2003; Rivkin, Hanushek, & Kain, 2005). These school inputs explain very little of the variation in test scores which is consistent with the idea that by school age, children are already locked into their development trajectory. The work of Heckman and colleagues provides some empirical evidence on the benefits of investments in early childhood development (Cunha & Heckman, 2006, 2007; Heckman, 2006, 2008). They demonstrate that investments in earlier stages affect a child's skills and abilities at later stages and that skills produced at earlier stages raise the *productivity* and *potential* of investment at later stages. Their work uses data collected in 1979 where the first measurement of children is ages 6 and 7. While these estimates provide valuable information on the skill formation process, they cannot capture the nuances of investment and skill formation in very early childhood development as we do here, and with data that more closely reflects the current population (i.e., children born in 2001). Given the critical role of early childhood development in conditioning the future success of individuals over the life-course, it is important to understand the determinants of improved cognitive function at very young ages at the population level in order to derive evidence-based policy recommendations.

The current study addresses this gap in the literature by providing detailed estimates of the child development production function (CDPF). We use rich data from a large national data set, the Early Childhood Longitudinal Study- Birth cohort (ECLS-B), to specify and estimate a comprehensive early childhood development production function which includes detailed information on familial inputs of time, goods, and parenting behavior between birth and kindergarten entry (ages 5-6). In doing so, we extend the existing literature on child development and education production functions in many directions. First, to our knowledge this is the first study to present population-representative estimates of the early childhood development production function which includes detailed information on both time and goods inputs for current and prior periods. Explicit inclusion of historic inputs is important because child development is cumulative and timing of inputs critical due to the physiological growth process where some periods of a child's early life are more sensitive than others. Second, because we have four waves of data, we can provide estimates of alternative, commonly-used specifications of the EPF such as the popular 'value-added model' and test the key assumption embodied in this specification—that a lagged value of the dependent variable is a sufficient statistic for the entire history of production function inputs. Third, we augment the standard economic inputs of 'time' and 'goods' with a measure of parent-child interaction from the child development literature which, as we show below, provides new and unique information in the CDPF and is amenable to policy intervention. Fourth, we present estimates of the demand for inputs, which is rarely done in such studies, but which allows us to distinguish between technical and allocative efficiency and to thus understand the pathway through which family background characteristics affect early childhood development, information which is also important for policy purposes. Finally, we address the issue of the endogeneity of inputs in the production function using dynamic panel data estimators, which explicitly recognizes that parents make decisions about the level and mix of inputs not only based on relative prices and income but also on the innate ability or endowment of the child, information known to the parent but not the researcher. Remedial behavior, for example, where parents apply extra inputs to children with lower endowment, would appear to indicate that more inputs lead to lower cognitive development if child-level (unobserved) heterogeneity is not accounted for. Addressing this endogeneity is rarely done in the EPF literature due to data constraints, but its neglect has obvious implications for inferences about the relative importance of inputs in early childhood development.

Theoretical Framework

a. The household production model

In economics, the theoretical basis for the CDPF stems from Becker's (1965) model of time allocation and household production. In this framework, the family is an economic unit that buys commodities from the market for consumption and allocates household resources (time, money) to produce goods and services at home, such as child cognitive development. This model is well-known and so we choose to omit a formal presentation of the model, but instead highlight two key elements of this model that play a crucial role in guiding theoretically consistent empirical work.

First, the production function for child development as envisioned in the theory is a purely technical relationship between inputs (e.g., reading books with child) on the one hand and output (e.g., child cognition) on the other. Its specification is guided by the human physiology of child development. Thus only factors that directly 'produce' child development enter into this relationship. However, variables that *influence* child development such as race or region or even parental education are often used in the empirical specification of the CDPF; yet these factors may not directly *produce* child development and so would not formally enter into the CDPF. For example, region of residence may reflect relative prices or access to information which would influence the *choice* of inputs but would not affect the *technical relationship* between the inputs and output.[14] Race may reflect access to resources which would also influence input choice, but not the technical relationship itself. On the other hand if race reflects cultural practices which in turn influences *how inputs are applied*, this reflects technical efficiency and would enter the CDPF. Similarly, parental education

[14] Region of residence may serve as a proxy for inputs that do directly affect cognition (such as environmental contamination or epidemiological conditions) in which case they may justifiably be included in the EPF.

may influence how inputs are applied whereby more educated parents are 'better teachers,' and thus reflect technical efficiency. On the other hand, education might simply influence the demand for inputs via parent's choices of input levels (e.g., quality or quantity of child care) or input bundles (e.g., time spent with child along with purchased goods for child), reflecting allocative efficiency. The point is that in the estimation of the CDPF, the distinction between the demand function specification and production function specification is an important one.

Second, the behavioral assumptions of the theoretical model—maximization of utility subject to technology and full-income constraints—yield 'reduced form' ordinary demand functions for each of the choice variables. The reduced-form is thus a function of all exogenous factors, such as prices and exogenous income or wealth. There are two distinct types of demand functions. Input demands govern the level of inputs chosen by parents to produce child cognition—these are derived demands and do not enter into the utility function directly. From a policy perspective, the input demand functions are of great interest as they describe the factors that determine input choice, particularly the role of income, prices, and information which can all be manipulated. Final demands are those items that enter directly into the utility function (leisure, consumption goods, and child cognition) and are functions of the same exogenous factors as the input demands, though the relative importance of these factors will vary across equations.

In this paper, we present empirical estimates of both the production function and the input demand equations and our choice of variables is guided by the theory as described here. In particular, factors that represent relative prices (such as region or state of residence) or income do not enter into the production function, but do enter the input demand equations.

We include race and parental education in both the production function and input demand equations to test whether they represent technical efficiency, allocative efficiency, or both.

b. Specification of the child development production function

Todd and Wolpin (2003, 2007) present a thorough discussion of alternative specifications of the CDPF and the assumptions embodied in these alternatives. In this section we briefly summarize the main issues involved in the estimation of these functions and their testable implications. Equation (1) describes a flexible form of the CDPF which posits that period *t* achievement (*T*) of the *ith* child is a function of contemporaneous and historical inputs (*X*) going back to birth (period 0), endowed mental capacity (μ), and a random error term (ε):

$$(1) \quad T_{it} = \alpha_1 * X_{it} + \alpha_2 * X_{it-1} + \alpha_3 * X_{it-2} + \ldots + \alpha_{i0} * X_{i0} + \mu_i + \varepsilon_{it}$$

Empirical implementation of (1) is hampered by data constraints because it is rare to have information on the entire history of inputs. Consequently, most empirical studies make the simplifying assumption that the effect of all prior inputs on contemporaneous cognition can be summarized by the prior period cognition score; in other words the lagged score is taken as a sufficient statistic for the entire history of inputs up to period *t-1*. This specification relates the current period score to current (or within) period inputs and the lagged score and is depicted in equation (2):

$$(2) \quad T_{it} = \alpha_1 * X_{it} + \gamma * T_{ijt-1} + \mu_i + \varepsilon_{it}$$

There are several assumptions embodied in (2) that are worth highlighting. First, the coefficients of all prior inputs are weighted by γ, the coefficient of lagged achievement. Thus, they have the same structure of 'decay'-- the impact of all inputs diminishes over time at the same rate.[15] While this might not lead to large bias if the lasting impact of prior inputs is small, it does rule out the possibility that the timing of inputs matters in early childhood, which is clearly not consistent with the neurobiology of development. Furthermore, the application of inputs during certain crucial developmental windows may have a direct effect on future cognition over and beyond their effect on prior period cognition—this possibility is also ruled out under the maintained assumption of the strict value-added model.

Finally, both (1) and (2) suffer from standard endogeneity bias since input choices made by parents will be governed by a child's endowed mental capacity (μ). Note that in (1) this endogeneity affects all inputs over time since μ appears in each and every period-specific production function and parents may thus respond to it in each period. Furthermore, the lagged dependent variable in (2) is also subject to endogeneity bias because it contains μ, and is thus correlated with the error term in (2). We return to the issue of endogeneity in Section 4 below.[16]

We follow the approach of Todd & Wolpin (2007) in our empirical analysis and test three distinct specifications of the production function as it relates to early childhood development. We begin with the classical value-added model with contemporaneous inputs (VAM), which is the most commonly used empirical specification in the literature. We compare this to the 'cumulative' specification given by equation (1) where the entire history of inputs is added directly to the production function. This allows us to check whether the sum of the coefficients of the inputs lines up with the coefficient on the lagged dependent variable, and to assess the rate of 'decay' of historical inputs. We then estimate the 'VAM-

[15] This assumption also applies to the historical impact of endowed mental capacity (μ).

[16] Todd & Wolpin (2003) discuss the issue of unmeasured inputs in the production function. To the extent that these are correlated with measured inputs they will also bias production function estimates in standard OLS-type analysis.

plus' which adds historic inputs to the VAM to test whether the lagged dependent variable is a sufficient statistic for the entire history of inputs. Together these alternative specifications allow us to assess the appropriateness of the assumptions embodied in the typical VAM models that are pervasive in the EPF and CDPF literature.

Data

We use the Early Childhood Longitudinal Study- Birth cohort (ECLS-B), a nationally representative sample of ~10,700 children born in the US in 2001 created by the National Center for Education Statistics. The goal of the ECLS-B was to examine the individual, family, and community level factors that are associated with children's health and developmental trajectories in the first six years of life. The sample was collected using a stratified probability sampling design by selecting from the cohort of births using Vital Statistics records. Metropolitan Statistical Areas created the primary sampling units (PSUs). Before selection, PSUs were stratified by region, median household income, proportion minority population, and metro versus non-metro area. The overall response rate for the study at the first wave was 77 percent.

The ECLS-B data are not only very rich in terms of the child and family variables but also include age-appropriate, direct child assessments at each wave, where each instrument used was decided by a technical review panel of child development experts. The data collection consisted of interviews with the primary caregiver (PCG; the biological mother in 99 percent of cases) and several direct child assessments at approximately nine months of age, 24 months, at preschool entry, and at kindergarten entry. The data also includes a computer-assisted personal interview administered to the parent respondent and in-home direct assessments of the child's development and caregiver child interaction patterns conducted by a trained administrator, and self-administered questionnaires for the resident father or male guardian, as well as the non-resident father. The survey weighted descriptive statistics of all variables included in our analyses are displayed in Table 3.1.

a. Child ability measures

Item Response Theory (IRT) was used to construct age-appropriate child ability measures in all four waves for all child ability assessments. Also known as latent trait theory, IRT assumes that the responses to the items on a test can be accounted for by latent traits, and sometimes even just a single latent trait (e.g., reading ability) (Lord, 1980). This approach uses a mathematical model of how test takers at different ability levels of the trait would respond to a given item, allowing a comparison of performance between different examinees (Crocker & Aligna, 2008). This makes it possible to create scores that can be comparable regardless of the assortment of items a child received during assessment. IRT is widely accepted method in education and is considered to be superior to classical test theory and is thus used in many diverse applications, especially for high stakes testing. For each child assessment outcome in each wave, ECLS-B developed separate measurement models using this approach (details of these models are available in ECLS-B Psychometric reports by Andreassen et al. 2005, 2007 and Najaran et al. 2010).

The nine-month and two-year child ability measures, mental ability, were generated from items adapted from the Bayley Scales of Infant Development-II (BSID-II) into the Bayley Short Form—Research Edition (BSF-R)(Bayley, 1993). The BSID-II is considered to be the most psychometrically sound standardized assessments available for young children, allowing the ECLS-B to use this assessment on both the nine-month and two-year measurement waves (Andreassen & Fletcher, 2005). The BSF-R mental scale measures children's cognitive functioning in areas such as vocalization, receptive language, object permanence, problem solving, and exploration of objects. We standardized the BSF-R scale measure at waves 1 and 2 and use these scores to represent age-appropriate child reading ability at 9 and 24 months.

The preschool and kindergarten cognitive outcome measure, reading ability, was a carefully selected pool of items from the Peabody Picture Vocabulary Test (PPVT), Comprehensive Test of Phonological Processing (CTOPP), pre-Las, and other instruments designed by IES for the ECLS-Kindergarten Cohort (S. E. Duncan & De Avila, 1998; Dunn & Dunn, 1997; Rock & Pollack, 2002; Wagner, et al., 1999). Taken together, the items administered to the participants measure basic early reading skills such as letter knowledge, letter-sound knowledge, print conventions, vocabulary, word recognition, developing interpretation and demonstrating a critical stance (Najarian, Snow, Lennon, & Kinsey, 2010). We standardized the reading scale scores at the preschool and kindergarten waves. Combined with the mental measures from the 9-month and 2 year wave, this reading measure is the dependent variable for all models.

b. Inputs and covariates

Parent characteristics

For most of the sample, the PCG is the child's biological mother, and therefore we conduct these analyses using maternal characteristics and refer to them as so. While the ECLS-B makes a great effort at collecting data from resident and non-resident fathers, the missingness on these data is considerable. In line with Todd & Wolpin (2007), the father's characteristics were not a significant predictor of child ability and are not included the analyses.

We include mother's age in years at time of assessment as a time-varying characteristic in the production function. Mother's educational attainment is included as a dichotomous variable indicating a college degree or higher. Unfortunately, the ECLS-B does not measure maternal intelligence directly through IQ tests or other similar assessments. To account for mother's intellectual ability, we include a dichotomous variable indicating whether the mother took calculus in high school. While not a perfect substitute, we think that this variable can account for some of the variation associated with mother's overall ability.

Parent behaviors

For the initial set of models, we use three inputs derived from the parent interview portion of the Home Observation for Measurement of the Environment (HOME). The HOME is a combination of parent-report and observational items that assesses the quality of cognitive stimulation and the emotional support that the child receives from the family (Caldwell & Bradley, 1984). The full instrument contains a battery of binary items organized into six subscales designed to assess: 1) the mother's responsiveness to the child, 2) the use of punishment and restriction, 3) the physical attributes of the home and neighborhood, 4) availability of toys and other play materials, 5) maternal involvement, and 6) variety in daily simulation.

Many large datasets use the HOME-Short Form version, which contains 21 items that are reduced from the original 45. The NLSY data used in Todd & Wolpin (2007) has the complete HOME-SF measure (sum of all binary items), which they include as their primary measure of the time and good inputs provided in the home. However, the HOME-SF was considered to be too lengthy for the ECLS-B in the context of the breadth of the information the study was collecting. Therefore NCES decided to include 3 parent interview (self-report) items in all four waves:[17] 1) How often do you sing songs to your child? 2) How often do you read books with your child?, and 3) How many books does the child have? Many items in the HOME have ordinal answer choices that receive binary scoring. Respectively, the binary coding of these inputs is as follows: 1 if greater than 3 times per week, 1 if greater than 3 times per week, 1 if greater than 9 books. These three variables are our time and goods input measures. We would have also included the interviewer observation items from the HOME scale, but the ECLS-B only conducted the in-home assessment in waves 1 and 2. We include the three parent interview items individually in our analyses in order to understand the mechanisms that produce child development in the home, as opposed to an overall or average effect of home characteristics.

Parent-child interaction. While the ECLS-B did not collect the set of binary items from interviewer home observations, a principal advantage of the ECLS-B is the inclusion of direct assessments of the parent-child interaction, a well-documented critical input for healthy child development. We use these in-home observational assessments of the parent-child interaction that were used to operationalize the PCG's parenting behavior as an input for production. This objective assessment of the parent-child relationship enables us to estimate more precisely the effects of the PCG's *parenting* behaviors by separating these from the effects of other inputs like educational attainment, parent's intelligence, purchased goods, time spent outside the home and income. In terms of policy and intervention, this provides a better examination of the mechanisms through which child development is produced in the home.

[17] Number of books was not measured at the nine-month wave.

Parent-child interactions were assessed in the nine-month, two-year and preschool waves. Two different age-appropriate instruments were used. The measure at the nine month wave, the Nursing Child Assessment Teaching Scale (NCATS), is a videotaped parent-child interaction where the parent is given a standard list of age-appropriate activities and is then asked to select one that the child was not yet able to do to complete with the child for assessment. These videotapes are coded by trained staff and then provide information on the parent-child relationship and the child's home environment (Andreassen & Fletcher, 2005). The NCATS has four parent subscales (Sensitivity to Cues, Response to Distress, Social-Emotional Growth Fostering, and Cognitive Growth Fostering), and two child subscales (Clarity of Cues, Responsiveness to Caregiver) (Barnard, 1997; Sumner & Spietz, 1994).

At the second and third waves (2 years and preschool), the NCATS was replaced by the 'Two Bags task' (TBT) because the TBT had a larger research base to support its use at older ages than the NCATS (Andreassen & Fletcher, 2007; Nord, Edwards, Andreassen, Green, & Wallner-Allen, 2006). The TBT is a modification of the National Institute for Child Health and Development's Three Bags which was used in the Early Head Start Research and Evaluation Project and in the National Institute of Child Health and Human Development (NICHD) Study of Early Child Care (Brady-Smith, O'Brien, Berlin, & Ware, 1999). This is also a videotaped, structured play and reading interaction between the parent and the child, where one bag has a book and the other has a play activity. This interaction is coded to describe the quality and quantities of interactive behaviors (Andreassen & Fletcher, 2007). The TBT rating scales include five parent rating scales (Emotional Support, Intrusiveness, Stimulation of Cognitive Development, Negative Regard, and Detachment) and three child rating scales (Child Engagement of Parent, Sustained Attention, and Negativity Toward

Parent). For consistency of the parenting behavior construct, we use the average of the two TBT parent subscales (Emotional Support and Stimulation of Cognitive Development) that capture comparable aspects of the parent's behavior measured by the NCATS in wave 1. We standardized these scores to generate the variable named *parent-child interaction*.

Child characteristics

Time-invariant child covariates include indicators for sex, race, and low birth weight.[18] We also include a time-varying child input that is coded 1 if the child attends some type of childcare outside of the home. While the processes that determine childcare are endogenous with respect to child development and family characteristics, children who are in childcare for some portion of their day necessarily have less exposure to the included home inputs than children who do not spend time out of the home environment. Therefore we condition for childcare attendance with the justification that it controls for actual exposure to the measured inputs in home production.

Results

a. Alternative specifications of the CDPF

We begin with an assessment of alternative specifications of the production function, using reading in kindergarten as our dependent variable. Table 3.2 shows the three specifications described in Section 2B plus several other variations to help us understand the relationship between prior inputs and child reading ability at kindergarten. All coefficients represent a standard deviation (SD) change in children's kindergarten reading ability.

[18] We also control for child's age in months at the time of assessment to account for between-child differences in assessment scores due to the differences in the actual timing of the assessment.

The VAM with contemporaneous inputs is the most common specification of the EPF in the literature and is shown in column 1--it relates current achievement to lagged achievement and current inputs. In this model, we assume that the lagged reading score summarizes the history of inputs and that the coefficients of all higher order lagged inputs are zero. The lagged reading score is strong and significant; a one SD increase in preschool reading score is associated with a 0.57 SD increase in kindergarten reading score. State dependence is therefore strong, but prior scores are not entirely deterministic of current scores. Not surprisingly, reading books to the child in kindergarten has a positive association with reading in kindergarten, but none of the other home inputs are significant. At the construct level, race is not significant. Having a college degree is positive and significant, but not mother's age or taking calculus.

Column 2 shows the cumulative model which, instead of including the lagged reading score as a summary of the child's history of inputs, includes the historical inputs explicitly and allows each input at each period to decay at different rates. Both the contemporaneous and lagged measure of reading books with the child at preschool and at 9 months are positive and significant as well. Even though the contemporaneous measures of singing songs and having more than 9 books in the home are not significant, their coefficients in the lagged periods are; singing songs at preschool age and at 2 years and number of books at preschool have a positive and significant association with reading in kindergarten. Notice that our two endowment measures, mother studied calculus in high school and low birthweight, are now statistically significant; the VAM in column (1) thus picks up the effects of prior inputs *and* familial endowments. The size of the coefficient for mother attending college also triples in this specification.

Following Todd & Wolpin (2007) we compare the sum of the coefficients of the lagged inputs with that of the lagged dependent variable in column 1 (0.57). The sum of the coefficients on all lagged inputs (.076+.10+.079+.091+.17+.14) is 0.656 which is greater than the effect of the inputs that is theoretically summarized by the lagged reading score. One important omission, however, is that the lagged reading score also incorporates the child's endowment. We otherwise measure this in our models using the low birthweight indicator. If low birthweight is included in the above summation, the effect of all combined lagged inputs and endowments equal 0.51, not far off from the lagged reading score coefficient of 0.57. This may suggest that the lagged dependent variable is a sufficient statistic for the child's historical home and individual endowments.

The VAM-plus combines the specifications in (1) and (2) by including the lagged reading ability, the contemporaneous inputs, and the lagged inputs. In this specification, we can test the primary assumption of the standard VAM; if the coefficients of the lagged inputs are not significant, the VAM assumption is valid. This is precisely what the results indicate in column 3; the coefficient of the lagged reading score is large and positive, at approximately the same strength as in (1), and none of the coefficients on the lagged inputs are significant. This provides additional support for the assumption of the VAM. The contemporaneous reading books coefficient is positive and significant, and this is the only significant input in the model. The effect of college persists, though it is two-thirds the size of what it was in the cumulative specification in (2); likewise the two endowment variables are statistically insignificant with the inclusion of the lagged dependent variable.

Columns 4-6 provide several additional specifications to help us understand the role of historical inputs and outcomes in the production of child cognition. In columns 4 and 5, we add two and then three lags of the dependent variable to the VAM. These are interesting models because they exclude inputs and only use data on outcomes—large administrative databases on K-12 student achievement scores do not contain data on home inputs but do contain multiple observations of test scores for each child so these are specifications which can be implemented with typical data sets used in the literature (Ballou, Sanders, & Wright, 2004; Lockwood, McCaffrey, Mariano, & Setodji, 2007; Rubin, Stuart, & Zanutto, 2004). The results show that there is very little change in the coefficient of the lagged dependent variable, though the two period lagged score is statistically significant with a coefficient of 0.07, and higher order lags are never significant. Column 6 presents a 'fully saturated' model where the entire history of inputs and lagged dependent variables are added to the model and this actually adds very little additional information to the model in column 4 or column 1; the contemporaneous measure of reading books continues to be significant and of roughly the same magnitude as in column 1, and the lagged dependent variable also returns a coefficient of 0.54 which is in line with the estimates in columns 1 and 4.

Our conclusion from these alternative specifications is that the VAM does remarkably well in capturing the history of inputs, and that without measures on historical inputs, one further lag of the dependent variable can add some additional information to the model. Of course from a behavioral and policy perspective, the cumulative model is the most informative because it identifies the precise inputs that matter for child development, as well as the timing of those inputs.

b. Parenting Skills

Both theory and empirical research from other disciplines demonstrate that the parent-child relationship, a dynamic with potential for change, is an important mechanism for predicting positive outcomes in children. Supportive relationships have a long-term influence on children's healthy development, contributing to optimal social, emotional, and cognitive development (Zeanah & Doyle-Zeanah, 2009). These relationships cultivate the development of curiosity, self-direction, persistence, cooperation, caring and conflict resolution skills, which are vital for school readiness (Greenough, Emde, Gunnar, Massinga, & Shonkoff, 2001; Kaplan-Sanoff, 2007).

Maternal characteristics of sensitivity and level of engagement with their child affects child outcomes independently of maternal IQ (Blair et al., 2008; Gershoff, Raver, Aber, & Lennon, 2007; Hackman, Farah, & Meaney, 2010; Tamis-LeMonda, Briggs, McClowry, & Snow, 2009). Different dimensions of caregiving have distinct contributions to child functioning (Moran, Forbes, Evans, Tarabulsy, & Madigan, 2008). Maternal sensitivity describes consistent and appropriate responses to the child and includes responsiveness, flexibility, warmth and teaching, are associated with children's school readiness and social competence, and are associated with positive child outcomes (Burchinal & Campbell, 1997; Carlson, 2003; Landry, Smith, Swank, Assel, & Vellet, 2001). Recent neuroscience studies find that aspects of the home environment and maternal sensitivity mediate observed SES disparities in child's executive functioning (2010). Additionally, measures of parental nurturance in early childhood uniquely predict memory function in middle school (Farah et al., 2008).

From a development science perspective the parent-child interaction is a direct measure of the actual home production technology. And unlike fixed characteristics of intelligence and education, parental sensitivity and engagement with their child during interaction is a manipulable behavior that is amenable to policy intervention.

To test these ideas we incorporate the parent-child interaction into the estimation of the CDPF. As described in the data section, this is an age-appropriate and reliable measure of the intellectually and emotionally supportive parent behaviors that were observed by the ECLS-B interviewer during parent interaction with their child for the first three waves. This is a more objective and valid measure of parent's time spent with children than from parent self-report inputs we use in the kindergarten models (reading books and singing songs). Indeed, pairwise correlations between the parent self-report inputs show only small to moderate associations between the interviewer observed and parent self-report measures for parenting activities and skills with no pairwise correlations above 0.25 (see Appendix F).

We select three specifications from Section 4, the VAM, the VAM-plus, and the VAM2-plus, and estimate them for *preschool reading only* since this parenting variable was not measured at kindergarten. We then add parenting to the specification. We also estimate the basic cumulative model for preschool reading (without parenting) for comparison to the kindergarten results.

Column 1 of Table 3.3 shows estimates for the cumulative model for preschool reading to check for consistency with the kindergarten model in column 2 of Table 3.2. Contemporaneous and historical measures of reading books and ownership of books are highly significant at this age, and only a one-period lag of singing songs is significant; this is roughly consistent with the kindergarten estimates except for contemporaneous ownership of books which is not significant in the kindergarten model.[19]

Columns 2 and 3 show the VAM without and then with the additional ‘parent-child interaction’ input. In column 2, the coefficient of the lagged dependent variable is 0.28, almost cut in half from the kindergarten model—state dependency appears to be much lower at younger ages. Note also that the endowment measures (mother took calculus and low birthweight) are significant at this age despite the inclusion of the lagged dependent variable, unlike the kindergarten models. In column 3, the parent-child interaction variable is statistically significant with a coefficient of 0.088, and its inclusion slightly reduces the effect of all the other contemporaneous inputs though they still remain statistically significant, which underscores the fact that this input adds new information to the production function. Its inclusion also slightly reduces the coefficients on the endowments and maternal education, though they each still remain statistically significant.

Columns 4 and 5 show the VAM plus lagged inputs models without and then with the inclusion of parent-child interaction. In column 4, only higher lags of reading books are statistically significant and the coefficient on the lagged dependent variable is fairly robust at 0.26. The inclusion of parent-child interaction in column 5 reduces slightly the effects of reading in the contemporaneous period and completely eliminates the effect of contemporaneous book ownership. Meanwhile parent-child interaction in all three periods is statistically significant with a large decay in the first lag (from 0.062 to 0.041) but a much smaller decay between the first and second lag. This is an important result in that it shows

[19] Of course, the kindergarten estimates do not include school inputs which can be an important source of omitted variable bias. This source of bias is less of a concern for the pre-school models.

that reading ability at preschool is directly associated with inputs applied at age 9 and 24 months, even after controlling for cognition at 24 months.[20]

c. Input Demand Functions

We provide coefficient estimates of the input demand functions organized by time period in Table 3.4. These are functions of all the exogenous variables in the model. We use state of residence interacted with rural as a measure of relative prices, and a dummy variable indicating household income in the top quartile as our measure of income rather than a continuous measure of income. We prefer this measure to actual reported income since reported income is both more susceptible to measurement error and presents a greater threat of endogeneity bias.

The strong statistical significance of parental education across all inputs suggests that education represents allocative efficiency in the production of young child cognition. The effects of parental education are similar across time but have particularly strong impacts on parent-child interaction and reading books. Income is strongly related to all inputs except singing songs but now there is a distinct pattern; income effects increase over time for parent-child interaction but decrease over time for reading books and number of books owned. Having had calculus in high school, which we interpret as an indicator of mother's mental endowment, is statistically significant for all inputs except parent-child interaction (even after controlling for income and education). This is an important result for public

[20] We also estimate each of the specifications in sections (a) and (b) separately by sex and by racial/ethnic groups as sensitivity tests. Overall, the magnitude, direction and significance of inputs were comparable across all groups and results were consistent with the full sample estimates. These results are available from the authors upon request.

policy because it indicates that parenting skills are not necessarily 'endowed' but can be taught.

The results in this table also show that on average, white children receive higher average levels of all inputs relative to black, Hispanic and Asian children, and these differences tend to increase as the child gets older. The disparity in achievement between blacks, Hispanics, and whites in the U.S. is the subject of much research and public policy (Carneiro, et al., 2005; Todd & Wolpin, 2007). The strength of our analysis is that it allows us to see whether differences in achievement are linked to differences in the demand for inputs, and the answer is not straightforward. For example, the production function estimates in Table 3.3 show that Asians tend to have higher than average test scores although their demand for inputs is lower in Table 3.4; on the other hand, the lower than average scores in Table 3.3 for Hispanics appears consistent with their lower demand for inputs in Table 3.4. This underscores the fact that while our production function specification is much more comprehensive than most, there are still important omitted inputs, including unobserved characteristics of parents themselves, whose impacts are captured in the coefficients of the observed inputs. We address this issue in the next section.

d. Endogeneity

So far our production function estimates have provided us with the 'total' effect of an input on child development in that it includes both the technical relationship between the observed input and output as well as the behavioral choices of parents and the effects of other unobserved inputs including characteristics of parents themselves. These estimates provide valuable descriptive information on the key associations with early childhood development but are unlikely to be purely causal. Todd & Wolpin (2003) argue that in many cases this is the relevant effect for public policy decision-making because parents will naturally respond to policy induced changes in the environment and this behavior should be accounted for when choosing between alternative policy options. However, they make their argument in the context of school-age children and policies that affect school inputs. For younger children, which is our focus here, the relative importance of school inputs is small if not negligible (if children do not attend childcare) and the primary source of bias derives from the correlation between input choice and the (unobserved to the researcher) endowment of the child (μ). We define *compensating* or *remedial* behavior when parents apply more or higher quality inputs to children with lower endowments, and *investment* behavior when parents apply more or higher quality inputs to children with higher endowments.

Consider a first-difference or child fixed effect version of the contemporaneous production function and the VAM:

(3) $\Delta T_{it} = \alpha_1 * \Delta X_{it} + \Delta \varepsilon_{it}$ *contemporaneous*

(4) $\Delta T_{it} = \alpha_1 * \Delta X_{it} + \gamma * \Delta T_{it-1} + \Delta \varepsilon_{ijt}$ *VAM*

In (3) and (4) the Δ term indicates the difference between the period indicated and one period prior. In equation (3), since the endowment (μ) is fixed over time (a plausible assumption given the short time frame considered here) the fixed-effect estimator purges the regression of this source of endogeneity and can provide consistent estimates of the effects of the inputs on child cognition.[21] However in (4), the fixed-effect estimator does not solve the endogeneity bias associated with the lagged dependent variable because the T_{t-1} component of ΔT_{t-1} is correlated with the ε_{t-1} component of $\Delta\varepsilon_t$. The correlation between ΔT_{it} and $\Delta\varepsilon_{it}$ can

[21] The fixed-effects version of the cumulative model is consistent under the maintained assumption that current inputs do not depend on past outcomes. This assumption may not be tenable.

be resolved by instrumenting the lagged difference in cognition with cognition lagged two periods (measured in levels) as well as any other time-varying exogenous variables (Arellano & Bond, 1991).[22] The potential problem with this estimator in cases where there are large samples but few time periods is that the first difference of the endogenous variable may be only weakly correlated with its lagged value. Blundell & Bond (1998) propose a more efficient Generalized Method of Moments (GMM) system estimator which entails estimating (4) jointly with (2) and using the lagged difference in cognition (ΔT_{it-1}) along with the lagged levels of other time varying exogenous variables as instruments in the levels equation in (2) (Arellano & Bover, 1995). Because we have multiple rounds of information on individual children we can pursue this system estimator as a way of obtaining consistent estimates of the VAM version of the CDPF. An additional potential strength of the fixed-effects instrumental variable approach is that it may also purge the regression of bias due to time-varying unobserved inputs that are correlated with the observed inputs included in the model.

Table 3.5 presents results of these panel models estimated on the preschool sample. Column (1) shows the fixed-effect estimates for the contemporaneous model where the effects of the inputs are now purged of parental behavioral choices. Comparison with column 3 of Table 3.3 shows that the parental behavioral pattern varies with the type of input. For example, parents display investment-type behavior with respect to reading books since the coefficient of reading books is higher in the OLS specification (0.18) than it is in the fixed-effects specification (0.084). On the other hand, parents display compensating behavior with respect to singing songs, quantity of books, and positive parenting. Compensating behavior

[22] We use state-level dummy variables as indicators of relative prices and interact these with age of the child (which is time varying since children are interviewed at different times of the year in each round) to generate additional time-varying exogenous identification.

with respect to parenting is especially interesting as it may indicate that parents are responsive to the endowment of the child in their parenting approach.

Columns 2 and 3 of Table 3.5 show the Arellano-Bond and Blundell-Bond specifications respectively, that control for the endogeneity of the lagged dependent variable. The Blundell-Bond estimator is indeed more efficient with a standard error on the lagged dependent variable about two-thirds of the size relative to the standard error in the Arellano-Bond estimator in column 2. The point estimates of the lagged dependent variable in column 3 (0.23), when compared to that from column 3 of Table 3.3 (0.27), indicate that only about 15 percent of the relationship between current and prior period cognition is due to parental behavior, and that on the whole this is investment-type behavior. These point estimates are significantly smaller than analogous estimates based on older children. For example the coefficient doubles to 0.56 when we use kindergarten-aged children (see Table 3.2), a coefficient that is the same as that reported by Todd & Wolpin (2007) for children age 12-13. These results underscore a key feature of child development of enormous policy relevance, that state dependency becomes stronger as a child becomes older.

The effects of inputs and the lagged test score shown in Table 3.5 are identified from changes over a three-year period in a child's life between the ages of nine and 48 months. What is driving these changes in inputs over this period and can such changes reasonably assumed to be exogenous and unrelated to a child's endowment? Using 'reading books' as an example, we characterize each child according to the pattern of 'reading books' applied to that child by his/her parent over the four waves. Column 1 of Table 3.6 lists each possible investment pattern where the first digit refers to the first wave (nine months); a value of 0 indicates that the input was not applied and a one indicates that it was applied. The most common patterns are ‘1111’ (36 percent) and ‘0111’ (15 percent) indicating the child was read to in all four periods or in the last three periods only. However, there is significant variation in the sample, with 57 percent showing some variation during this window, and 18 percent switching status twice.

How does this variation in reading books correlate with variation in children’s reading scores? Figure 3.1 plots reading scores at each wave by the parent’s reading investment patterns. We show the two extreme cases, never reading (0000), always reading (1111) and all other reading patterns for comparison**.** Children in all three groups start out with fairly equal scores at the 9-month wave with about two-tenths of a standard deviation difference between groups. By kindergarten, those children who have been read to in each period score nearly 1 SD higher in reading ability compared with children who have not had any reading investment. Note that in all cases there is a steep increase in reading scores between pre-school and kindergarten, but the rate of this increase is the same for those who were never or always read to, and is higher for those who had some reading. This suggests that formal schooling is most productive for those with at least some exposure to reading.

Table 3.7 shows means for test scores and frequencies of other characteristics by investment pattern to examine whether there are systematic differences in investment based on child endowment or parental characteristics. There appears to be no relationship among LBW of the child, whether mother took calculus, and reading to the child at nine months suggesting that early application of this input is not necessarily a response to the child’s endowment nor an endowed characteristic of the mother herself. This is highlighted for LBW in Figure 3.2, where we categorize children by the time period in which their parent initiated reading. Parents with children who are LBW do not appear to have differential reading initiation behaviors, suggesting that the decision to initiate reading is not in response to their child's endowment (or at least to this particular measure of endowment).

The frequencies in Table 3.7 show a positive association between socioeconomic status and reading books to the child. Parents who read to their child in all or most periods (top rows of the table) are more frequently in the highest income quartile, have a college degree, and are not an ethnic minority. This supports the idea that reading to your child is a learned behavior, and that the importance of reading might be a learned trait. Accordingly, these high investing parents also have higher than average parent-child interaction scores at 9 months. Note that children in the bottom three rows are particularly at risk. Though they score around the mean for 'endowments' such as LBW and having a mother who took calculus, scores for parent-child interaction are over one-third of a standard deviation lower than the mean, and lose over one-third of a standard deviation in reading score by 24 months; for those in the bottom row this reading loss cannot be recuperated in kindergarten.

In Figure 3.3 we plot average child reading score at each wave by the age at which parents initiated reading to their children in to understand whether early initiation of reading is related to a child's ability. This figure illustrates two main points. First, though most children have similar reading abilities at nine months, children who are read to at nine months have slightly higher initial reading scores, an indication of *investment*-like behavior. However, children of parents who delay reading until 24 months have the same initial reading ability as children whose parents delay reading until preschool or later. In other words, among those who begin reading to children after nine months, there is no systematic relationship between the timing of reading and initial reading ability. On the other hand, the timing of reading initiation is clearly related to both the level and trajectory of a child's reading score. Finally, note the steep rate of increase in scores at kindergarten among children who have been exposed to *some* reading prior to school-entry. Together our results suggest a causal effect of having some exposure to reading prior to school-entry on kindergarten test scores.

Discussion

We report some of the first population-level estimates of the child development production function. The results offer rich insights into the nature of child development, the benefits of alternative specifications of the production function, the type and timing of inputs that are important for child development, the role of family characteristics and endowments in allocative and technical efficiency, and the potential policy options for enhancing the life chances of children.

Our exploration of alternative specifications of the production function indicate that the VAM does well in capturing the history of inputs as well as endowments, and that one further lag can add additional information to the model. However, the VAM is extremely limited as a policy tool because it does not provide insights into the 'black box' of behaviors, including input choices and the timing of critical inputs that determine cognition. In this respect the cumulative model is preferred, but it is data intensive and unlikely to be widely estimable at the population level.

Our discussion of results focuses on the preschool estimates because home inputs are more relevant at this age compared to kindergarten when children begin formal schooling. Results from the cumulative model for preschool (Table 3.3) reading cognition indicate that lagged inputs for reading books, singing songs and ownership of books are all important. Particularly noteworthy here is that the level of *all* these inputs applied at 24 months of age are statistically significant determinants of cognition at 48 months, and reading books as early as 9 months has a direct association with cognition at 48 months. Consequently, public policy would do well to focus efforts at parents of very young children, but the descriptive analysis suggests that any exposure to reading prior to kindergarten is likely to have beneficial effects on subsequent reading scores in kindergarten.

One of our main innovations is the introduction of parenting behavior and the parent-child interaction as a key input in the child development production function. We show that this input brings additional information beyond the other inputs and endowments to the production process, and both contemporaneous and historical levels of this input, as far back as 9 months, are direct and important determinants of cognition at 48 months, even after controlling for cognition at 24 months. Analysis of the demand for this input indicates that it is also amenable to policy because it is not determined by parental genetic endowment, but rather by education and income. Moreover the relative importance of income and education as a determinant of this input increase as the child ages, indicating once again that interventions to influence parenting skills should occur as early as possible. The results also indicate that parents adopt remedial or compensatory behavior with regard to this input, so that increased awareness about parent-child interaction and the parent's sensitivity and engagement with their child may have a larger impact on children with lower endowments.

The comparison between the determinants of input demand and the production function provide guidance on allocative versus technical efficiency in child development production. We find that maternal education plays both roles and that its relative importance is constant across all ages of the child. Income is also an important determinant of input use, with the largest income effects displayed for positive parenting and unlike for maternal education, the effect of income gets larger for this input as the child ages. Our analysis of input demands also shows significant lower demand for all inputs by Hispanic and black parents, including positive parenting. However this lower use of inputs does not translate into immediate differences in cognition at pre-school or even kindergarten between blacks and whites, though such differences are well documented at older ages (Carneiro, et al., 2005; Todd & Wolpin, 2007). It is possible that these later life ethnic disparities in achievement among children may be due in part to lower use of critical inputs at very early ages because of the lasting effect of these inputs, but we cannot deduce that from the results presented here and it remains a pending research question.

The investigation into endogeneity of input choice reveals that overall, parents display investment type behavior and about 15 percent of the relationship between cognition at preschool and 24 months is due to these parental behaviors regarding the level and mix of inputs. The detailed descriptive analysis suggests that this endogeneity may be driven by the group of children who are read to from age nine months on who have higher initial reading ability than the rest of the sample. On a more positive note, the relationship between contemporaneous and prior period cognition is significantly smaller (by half) prior to school entry, implying that children are much more likely to be locked into a development path after entering school, which again demonstrates that the early childhood years are an efficient period for policy intervention to correct deficiencies that can alter a child's life-chances.

Our analysis has provided rich new information on many features of the child development production process. We identify three key take-home messages from the results presented here. First, the application of inputs such as parenting, reading books and singing songs as early as 9 months of age have an important effect on reading cognition in kindergarten. Second, the parent-child interaction is an important input in the development process and one that is particularly amenable to policy because it is unrelated to maternal endowment. The third and most important message is that due to the cumulative nature of cognitive development, the most efficient time to intervene is at very young ages, as young as 9 months of age. Not only do inputs at this time period have lasting effects on future cognition, but our results show that the likelihood of locking into a development trajectory is significantly greater at 60 months relative to even 12 months earlier.

TABLE 3.1: DESCRIPTIVE STATISTICS BY MEASUREMENT WAVE (WEIGHTED)

	(1) Kindergarten	(2) Preschool	(3) 2 years	(4) 9 months
Sings songs	0.66	0.77	0.87	0.88
	(0.48)	(0.42)	(0.33)	(0.32)
Reads books	0.74	0.73	0.72	0.54
	(0.44)	(0.45)	(0.45)	(0.50)
10 or more books in home	0.92	0.91	0.84	0.50
	(0.28)	(0.29)	(0.36)	(0.50)
Reading scale score (std.)	0.13	-0.027	0.15	0.18
	(0.92)	(0.96)	(0.97)	(0.97)
Male	0.51			
	(0.50)			
Black	0.14			
	(0.35)			
Hispanic	0.25			
	(0.43)			
Asian	0.026			
	(0.16)			
Other race	0.045			
	(0.21)			
Low birthweight	0.075			
	(0.26)			
Rural	0.15			
	(0.35)			
Northeast	0.17			
	(0.37)			
West	0.24			
	(0.43)			
Midwest	0.22			
	(0.42)			
South	0.37			
	(0.48)			
Mother's age	28.3			
	(6.37)			
Calculus in HS	0.094			
	(0.29)			
College	0.27			
	(0.45)			
Top income quartile	0.30	0.28	0.22	0.20
	(0.46)	(0.45)	(0.42)	(0.40)
Observations	6700	8300	8900	10200

SDs in parentheses
Observations rounded to the nearest 50 per ECLS-B security requirements

TABLE 3.2: ESTIMATES OF THE CDPF FOR READING IN KINDERGARTEN

	(1) VAM	(2) Cumulative	(3) VAM-plus lagged inputs	(4) VAM - 2 lags	(5) VAM - 3 lags	(6) VAM-plus with 3 lags
Sings songs - Kindergarten.	0.023	0.012	0.0025			0.014
	(0.029)	(0.035)	(0.029)			(0.031)
Reads books - Kindergarten	0.14*	0.17*	0.14*			0.13*
	(0.029)	(0.035)	(0.031)			(0.033)
10 or more books in home - Kindergarten	0.030	0.062	-0.0088			0.0030
	(0.050)	(0.067)	(0.050)			(0.054)
Sings songs - Preschool		0.076*	0.042			0.038
		(0.032)	(0.024)			(0.026)
Sings songs - 2 yrs.		0.10*	0.037			0.022
		(0.050)	(0.044)			(0.049)
Sings songs - 9 mo.		0.037	0.025			0.0068
		(0.049)	(0.041)			(0.042)
Reads books - Preschool		0.079*	0.0093			0.013
		(0.038)	(0.034)			(0.032)
Reads books - 2 yrs.		0.060	-0.0018			-0.018
		(0.044)	(0.037)			(0.038)
Reads books - 9 mo.		0.091*	-0.016			-0.015
		(0.037)	(0.032)			(0.032)
10 or more books in home - Preschool		0.17*	0.087			0.081
		(0.068)	(0.055)			(0.061)
10 or more books in home - 2 yrs.		0.037	-0.027			-0.026
		(0.045)	(0.039)			(0.041)
Reading scale score (std.) - Preschool	0.57*		0.56*	0.56*	0.56*	0.54*
	(0.022)		(0.023)	(0.021)	(0.022)	(0.024)
Reading scale score (std.) - 2 yrs.				0.077*	0.075*	0.072*
				(0.017)	(0.017)	(0.017)
Reading scale score (std.) - 9 mo.					0.018	0.019
					(0.027)	(0.027)
Male	-0.037	-0.11*	-0.034	-0.029	-0.029	-0.019
	(0.025)	(0.030)	(0.026)	(0.025)	(0.025)	(0.026)
Black	0.0071	-0.025	0.015	0.00094	0.0021	0.040
	(0.039)	(0.040)	(0.042)	(0.044)	(0.044)	(0.046)
Hispanic	0.052	-0.10*	0.062	0.065	0.065	0.092*
	(0.040)	(0.047)	(0.040)	(0.046)	(0.045)	(0.043)
Asian	0.26*	0.51*	0.27*	0.27*	0.27*	0.30*
	(0.052)	(0.056)	(0.052)	(0.058)	(0.058)	(0.061)
Other race	-0.052	-0.079	-0.038	-0.051	-0.045	-0.020
	(0.071)	(0.078)	(0.069)	(0.077)	(0.077)	(0.077)
Low birthweight	-0.047	-0.14*	-0.050	-0.0085	0.00043	-0.0048
	(0.028)	(0.034)	(0.028)	(0.030)	(0.030)	(0.031)
College - 9 mo.	0.13*	0.38*	0.12*	0.14*	0.14*	0.11*
	(0.029)	(0.033)	(0.030)	(0.030)	(0.031)	(0.031)
Calculus in HS	0.061	0.12*	0.057	0.089*	0.088*	0.071
	(0.041)	(0.050)	(0.041)	(0.043)	(0.042)	(0.042)
Observations	6300	6600	6250	5900	5900	5800
F	146.7	45.0	81.6	176.2	142.0	64.0

SE's in parentheses; * p<.05; Obs. rounded to nearest 50 per ECLS-B security requirements

TABLE 3.3: ESTIMATES OF THE CDPF FOR READING IN PRESCHOOL

	(1) Cumulative	(2) VAM	(3) VAM with parenting	(4) VAM-plus lagged inputs	(5) VAM-plus with parenting	(6) VAM-plus with 2 lags	(7) VAM-plus with 2 lags & parenting
Sings songs - Preschool	0.052	0.073*	0.067*	0.041	0.024	0.039	0.024
	(0.027)	(0.029)	(0.030)	(0.028)	(0.033)	(0.028)	(0.033)
Sings songs - 2 yrs.	0.096*			0.066	0.062	0.068	0.063
	(0.035)			(0.037)	(0.045)	(0.037)	(0.045)
Sings songs - 9 mo.	0.0016			-0.010	-0.039	-0.013	-0.041
	(0.034)			(0.034)	(0.041)	(0.034)	(0.042)
Reads books - Preschool	0.17*	0.21*	0.18*	0.16*	0.13*	0.16*	0.13*
	(0.029)	(0.029)	(0.030)	(0.032)	(0.037)	(0.032)	(0.037)
Reads books - 2 yrs.	0.13*			0.10*	0.090*	0.10*	0.091*
	(0.032)			(0.034)	(0.037)	(0.034)	(0.037)
Reads books - 9 mo.	0.12*			0.088*	0.11*	0.085*	0.11*
	(0.027)			(0.026)	(0.037)	(0.026)	(0.037)
10 or more books - Preschool	0.14*	0.16*	0.12*	0.12*	0.029	0.12*	0.028
	(0.036)	(0.042)	(0.041)	(0.043)	(0.056)	(0.043)	(0.056)
10 or more books in home - 2 yrs.	0.13*			0.077	0.064	0.077	0.063
	(0.040)			(0.041)	(0.046)	(0.041)	(0.047)
Positive parenting (TB subscales) - Preschool			0.088*		0.062*		0.062*
			(0.013)		(0.017)		(0.017)
Positive parenting (TB subscales) - 2 yrs.					0.041*		0.040*
					(0.020)		(0.020)
Positive parenting (NCATS) - 9 mo.					0.036*		0.035*
					(0.015)		(0.014)
Reading scale score (std.) - 2 yrs.		0.28*	0.27*	0.26*	0.26*	0.25*	0.25*
		(0.013)	(0.016)	(0.014)	(0.020)	(0.015)	(0.020)
Reading scale score (std.) - 9 mo.						0.038	0.040
						(0.024)	(0.029)
Male	-0.14*	-0.044	-0.048	-0.049	-0.044	-0.046	-0.042
	(0.026)	(0.026)	(0.026)	(0.026)	(0.033)	(0.026)	(0.033)
Black	-0.051	0.0055	0.017	0.039	0.082	0.037	0.081
	(0.033)	(0.033)	(0.034)	(0.033)	(0.043)	(0.034)	(0.043)
Hispanic	-0.25*	-0.19*	-0.17*	-0.16*	-0.086	-0.16*	-0.088
	(0.037)	(0.034)	(0.037)	(0.035)	(0.044)	(0.035)	(0.044)
Asian	0.35*	0.38*	0.45*	0.41*	0.53*	0.41*	0.52*
	(0.046)	(0.045)	(0.055)	(0.045)	(0.066)	(0.045)	(0.066)
Other race	-0.013	0.036	0.060	0.045	0.059	0.017	0.061
	(0.057)	(0.057)	(0.061)	(0.057)	(0.061)	(0.046)	(0.060)
Low birthweight	-0.19*	-0.081*	-0.074*	-0.084*	-0.085*	-0.064*	-0.063
	(0.027)	(0.025)	(0.025)	(0.024)	(0.032)	(0.024)	(0.035)
College	0.51*	0.46*	0.44*	0.43*	0.36*	0.42*	0.36*
	(0.034)	(0.035)	(0.038)	(0.035)	(0.041)	(0.034)	(0.041)
Calculus in HS	0.11*	0.13*	0.10*	0.12*	0.037	0.11*	0.035
	(0.034)	(0.037)	(0.040)	(0.039)	(0.044)	(0.039)	(0.045)
Observations	8200	7550	6700	7550	5050	7550	5050
F	110.1	194.2	155.2	119.7	65.6	102.4	62.6

SEs in parentheses; * p<.05; Obs. rounded to the nearest 50 per ECLS-B security requirements

TABLE 3.4: ESTIMATION OF INPUT DEMANDS FOR READING AT PRESCHOOL, 2 YEARS, AND 9 MONTHS OF AGE

	Preschool				24 months				9 months		
	(1) Sing songs	(2) Read books	(3) 10 or more books	(4) Parent-child	(5) Sing songs	(6) Read books	(7) 10 or more books	(8) Parent-child	(9) Sing songs	(10) Read books	(11) Parent-child
Male	-0.093*	-0.050*	-0.011*	-0.018	-0.038*	-0.035*	-0.0100	-0.090*	-0.011	-0.022	-0.048*
	(0.010)	(0.012)	(0.0045)	(0.027)	(0.0082)	(0.010)	(0.0084)	(0.026)	(0.0073)	(0.015)	(0.021)
Black	-0.0088	-0.25*	-0.16*	-0.27*	-0.021	-0.23*	-0.20*	-0.30*	-0.028*	-0.15*	-0.10*
	(0.019)	(0.023)	(0.020)	(0.046)	(0.021)	(0.026)	(0.021)	(0.044)	(0.013)	(0.023)	(0.045)
Hispanic	-0.12*	-0.25*	-0.18*	-0.42*	-0.077*	-0.27*	-0.30*	-0.34*	-0.043*	-0.22*	-0.32*
	(0.016)	(0.022)	(0.016)	(0.047)	(0.019)	(0.021)	(0.024)	(0.039)	(0.012)	(0.019)	(0.049)
Asian	-0.19*	-0.25*	-0.34*	-0.46*	-0.12*	-0.30*	-0.43*	-0.65*	-0.093*	-0.26*	-0.36*
	(0.024)	(0.030)	(0.032)	(0.060)	(0.023)	(0.026)	(0.032)	(0.049)	(0.016)	(0.028)	(0.049)
Other race	0.014	-0.089*	-0.049*	-0.074	0.0062	-0.059*	-0.068*	-0.086	0.048*	-0.055	-0.038
	(0.024)	(0.027)	(0.020)	(0.059)	(0.020)	(0.028)	(0.026)	(0.054)	(0.012)	(0.031)	(0.053)
Low birthweight	0.0092	0.011	-0.0040	0.0014	0.0041	0.00016	-0.0089	-0.039	0.0090	0.0031	-0.084*
	(0.012)	(0.014)	(0.0055)	(0.033)	(0.0097)	(0.014)	(0.0094)	(0.026)	(0.0080)	(0.014)	(0.031)
Calculus in HS	0.069*	0.044*	0.015*	0.053	0.032*	0.035*	0.028*	0.054	0.051*	0.075*	0.023
	(0.017)	(0.020)	(0.0057)	(0.052)	(0.013)	(0.018)	(0.0094)	(0.059)	(0.011)	(0.021)	(0.050)
College	0.059*	0.19*	0.051*	0.25*	0.046*	0.14*	0.083*	0.31*	0.052*	0.13*	0.29*
	(0.014)	(0.016)	(0.0064)	(0.036)	(0.011)	(0.014)	(0.0084)	(0.037)	(0.010)	(0.021)	(0.034)
Top income quartile	0.016	0.055*	0.051*	0.26*	0.0057	0.093*	0.072*	0.18*	0.011	0.10*	0.12*
	(0.017)	(0.020)	(0.0057)	(0.047)	(0.015)	(0.019)	(0.010)	(0.045)	(0.015)	(0.020)	(0.039)
Observations	8850	8850	8850	7550	9800	9800	9800	7650	10700	10700	8650
F	20.4	36.0	41.2	37.6	7.44	35.6	24.0	68.9	10.7	24.7	40.6

Marginal effects; Standard errors in parentheses
* p<.05
Observations rounded to the nearest 50 per ECLS-B security requirements

TABLE 3.5: PANEL DATA MODELS FOR READING IN PRESCHOOL

	(1) Child fixed effects	(2) Arellano-Bond + parent-child	(3) Blundell-Bond + parent-child
Sings songs	0.11*	-0.77	-0.12
	(0.033)	(0.48)	(0.26)
Reads books	0.084*	-0.70	-0.51*
	(0.026)	(0.48)	(0.23)
10 or more books in home	0.28*	2.81*	1.22*
	(0.045)	(0.52)	(0.29)
Parent-child interaction	0.13*	0.13	-0.068
	(0.012)	(0.19)	(0.10)
Lagged reading scale score (std.)		0.18*	0.23*
		(0.030)	(0.020)
Observations	21300	14000	14050
F	26.9		

Standard errors in parentheses * p<.05. Observations rounded to the nearest 50 per ECLS-B security requirements. Coefficients represent a standard deviation change in child reading skills at 48 months of age.

TABLE 3.6: FREQUENCIES OF PARENT READING INVESTMENT PATTERNS OVER THE FOUR WAVES OF DATA

Reading pattern	Frequency	Percent
1111	500	7.17
1110	350	5.04
1101	200	2.77
1100	400	5.37
1011	250	3.62
1010	300	4.35
1001	200	3.19
1000	1,050	15.09
0111	100	1.68
0110	100	1.64
0101	50	0.93
0100	250	3.43
0011	150	2.14
0010	250	3.32
0001	250	3.78
0000	2,500	36.49
Total	6,950	

Observations are rounded to the nearest 50 per ECLS-B security requirements. Children are grouped by the pattern of ‘reading books’ applied by his/her parent over the four waves, where the first digit refers to the first wave (nine months); a value of 0 indicates that the input was not applied and a one indicates that it was applied.

TABLE 3.7: FAMILY AND CHILD CHARACTERISTICS BY READING PATTERN (COLUMN PERCENTAGES)

Reading pattern	In top income quartile	Mother has college degree	Parent-child interaction at 9 months	Black	Hispanic	White	Mother took Calculus	Low birthweight	Reading - 9 months	Reading - 2 years	Reading - 4 years	Reading - kindergarten
1111	33.29	45.4	0.28	7.5	11.57	58.27	8.72	25.26	0.09	0.30	0.33	0.44
1110	18.75	26.17	0.13	16.41	16.02	47.27	11.33	28.13	0.08	0.13	-0.01	0.13
1101	11.06	15.04	0.02	23.89	19.91	30.09	10.62	30.53	0.14	-0.14	-0.19	-0.04
1100	14.58	10.42	-0.22	20.14	29.17	31.94	7.64	21.53	0.01	-0.01	-0.27	-0.09
1011	19.07	21.19	0	16.53	24.15	33.47	13.98	19.07	.0389	-0.10	0.00	0.23
1010	14.52	14.52	-0.27	19.35	24.19	29.03	8.06	25.81	0.03	-0.19	-0.34	-0.20
1001	8.33	18.52	-0.22	27.78	33.33	13.89	13.89	25.93	0.09	-0.31	-0.27	0.01
1000	6.19	10.62	-0.16	27.43	38.05	11.5	7.96	28.32	0.08	-0.16	-0.41	-0.30
0111	26.3	35.19	0.06	9.87	16.81	45.85	6.74	24.73	-0.11	0.05	0.08	0.26
0110	11.43	16.19	-0.14	18.1	20.48	28.57	8.57	21.43	0.03	-0.07	-0.16	-0.04
0101	13.13	14.81	-0.17	21.89	26.94	27.27	11.45	27.27	-0.05	-0.17	-0.23	0.04
0100	8.5	9.72	-0.14	27.53	26.72	25.1	10.53	25.1	-0.05	-0.23	-0.30	-0.14
0011	12.67	15.15	-0.16	14.88	26.72	32.78	8.26	21.21	-0.10	-0.33	-0.24	0.03
0010	4.32	10.81	-0.38	28.11	31.35	22.16	12.97	26.49	-0.08	-0.38	-0.31	-0.15
0001	11.14	14.08	-0.39	22.29	31.96	18.77	9.97	24.93	.0499	-0.30	-0.39	-0.06
0000	4.26	6.18	-0.38	36.46	32.84	13.22	7.46	24.52	-0.09	-0.40	-0.48	-0.35
Sample mean	*21.47*	*28.73*	*0.028*	*15.53*	*19.92*	*40.81*	*9.05*	*24.94*	*0.01*	*0.02*	*0.02*	*0.17*
Total number of children who have a value of 1 for this characteristic	1,450	1,950		1,050	1,350	2,750	600	1,700				

Observations rounded to the nearest 50 per ECLS-B security requirements

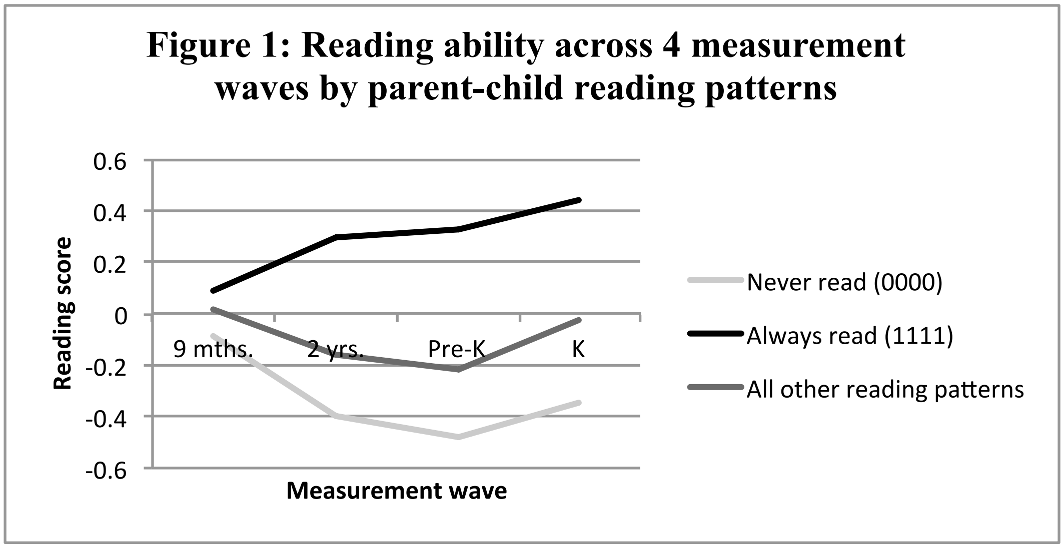


FIGURE 3.1: READING ABILITY ACROSS 4 MEASUREMENT WAVES BY PARENT-CHILD READING PATTERNS

Children are grouped by the pattern of 'reading books' applied by his/her parent over the four waves, where the first digit refers to the first wave (nine months); a value of 0 indicates that the input was not applied and a one indicates that it was applied. The y-axis represents the average reading ability score for children in that reading pattern at each of the four measurement waves.

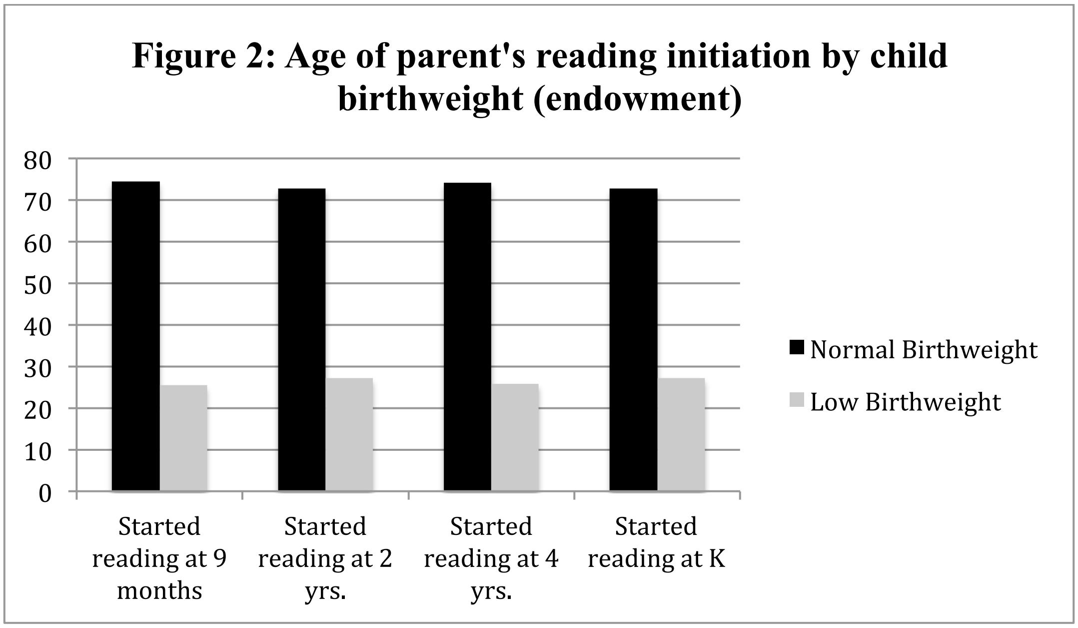


FIGURE 3.2: AGE OF PARENT'S READING INITIATION BY CHILD BIRTHWEIGHT (ENDOWMENT)

Children are grouped by the time period (measurement wave) in which their parent initiated reading. Each set of bars represents the total subgroup of children in the sample whose parents initiated reading in that period. Therefore, each of the grey bars represent the proportion of children who were born with low birthweight out of all children whose parents initiated reading in that period.

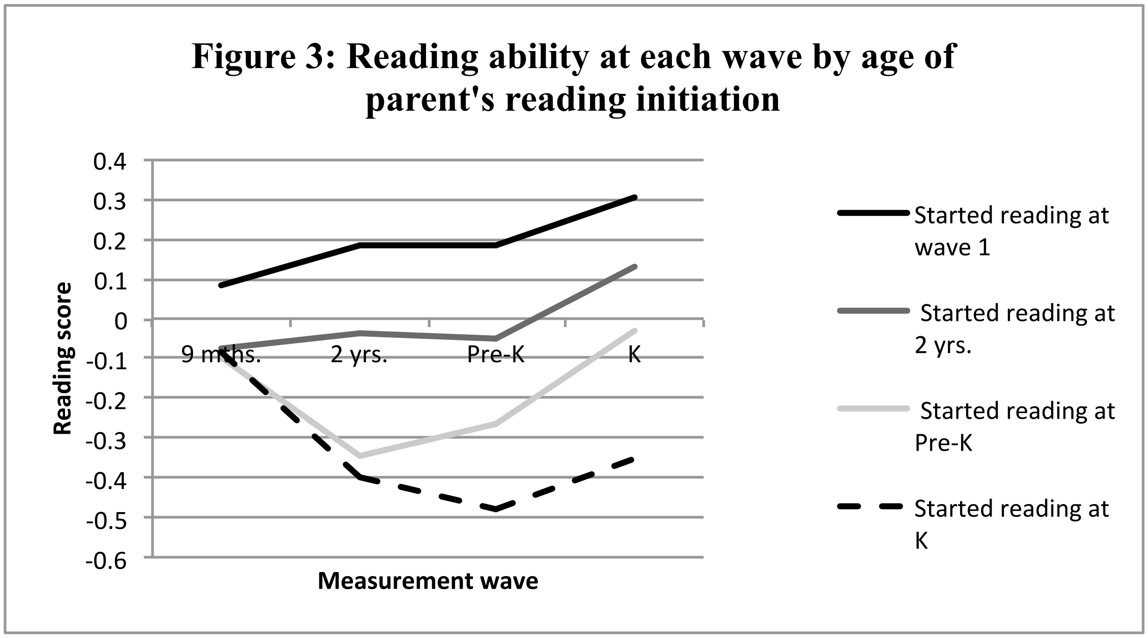


FIGURE 3.3: READING ABILITY AT EACH WAVE BY AGE OF PARENT'S READING INITIATION

Children are grouped by the time period (measurement wave) in which their parent initiated reading. The y-axis represents the average reading ability score for children in that reading initiation group at each of the four measurement waves.

Appendix A:

NC Counties by HRL Index Ranking

County Name	Index Score	County Name	Index Score
Robeson County	23	Orange County	15
Halifax County	21	Graham County	15
Randolph County	21	Beaufort County	15
Vance County	21	Wake County	15
Edgecombe County	21	Ashe County	15
Cleveland County	21	Lincoln County	15
Harnett County	21	Hoke County	14
Columbus County	20	Macon County	14
Gaston County	20	McDowell County	14
Lenoir County	20	Chowan County	14
Pitt County	20	Washington County	14
Davidson County	19	Warren County	14
Cumberland County	19	Northampton County	14
Wilson County	19	Bertie County	13
Rutherford County	19	Perquimans County	13
Wayne County	19	Mitchell County	13
Guilford County	18	Moore County	13
Sampson County	18	Greene County	13
Cherokee County	18	Pasquotank County	13
Surry County	18	Caswell County	13
Rowan County	18	Transylvania County	13
Forsyth County	18	Hertford County	13
Richmond County	18	Tyrrell County	13
Catawba County	18	Haywood County	12
Anson County	18	Pender County	12
Craven County	18	Alleghany County	12
Scotland County	18	Henderson County	12
Cabarrus County	17	Yadkin County	12
Buncombe County	17	Yancey County	12
New Hanover County	17	Alexander County	12
Durham County	17	Swain County	12
Alamance County	17	Hyde County	12
Iredell County	17	Chatham County	12
Rockingham County	17	Avery County	11
Bladen County	17	Davie County	11
Onslow County	17	Madison County	11
Nash County	17	Jones County	11
Lee County	17	Jackson County	11
Brunswick County	17	Person County	11
Caldwell County	17	Pamlico County	10
Burke County	17	Clay County	10
Johnston County	16	Granville County	10
Union County	16	Stokes County	10
Montgomery County	16	Watauga County	9
Stanly County	16	Carteret County	9
Duplin County	16	Dare County	9
Martin County	16	Gates County	8
Wilkes County	16	Polk County	6
Mecklenburg County	16	Camden County	6
Franklin County	15	Currituck County	6

Key
HRL Year 1
HRL Year 2
No HRL Treatment

Appendix B:

States listed by the number of agencies through which they implement the seven components of ECCE policy (2008): *Child care subsidies, Head Start Collaboration, Licensing, Regulation, Pre-k, IDEA Section 619, IDEA Part C*.

Number of State agencies	State abbreviations
1	MD
2	IA, ID, IN, ME, MI, MN, MT, ND, NV, OR, PA, SD, TN, WA
3	AK, AZ, CA, CO, DE, HI, IL, KS, LA, MA, NC, NE, NH, NM, OH, OK, RI, SC, VA, VT, WI, WY
4	AR, CT, GA, KY, MO, NJ NY, UT, WV
5	AL, MS
6	FL, TX

Source: *Early Child Care and Education: State Governance Structures,* Office of Child Care, Administration for Children and Families, Department of Health and Human Services

Appendix C:
Pairwise correlation of all state-level variables included in analyses

	Dispersion of ECCE Governance (1-5 scale)	Highly dispersed (>3)	Pct. women in legislature	Government ideology index (+more liberal)	Governor is democrat	Percent population Hispanic	Percent population black	Population in thousands	Income per capita	CDF scorecard ranking	CDF Congressional scorecard (CDF) (+bette	GSP in millions	Change in K-12 Per-pupil exp. 2002-2007	Number of poor children ages 0-5	Difference b/w state and fed. min wage	Maximum TANF benefit for family/year.	Combined CCDF + HS per-pupil expenditures	K-12 per-pupil expenditures (thousands)
Dispersion of ECCE Governance (1-5 scale)	1																	
Highly dispersed (>3)	0.73	1																
Pct. women in legislature	-0.32	-0.24	1															
Government ideology index (+more liberal)	-0.33	-0.34	0.28	1														
Governor is democrat	-0.35	-0.31	0.11	0.64	1													
Percent population Hispanic	0.22	0.18	0.37	0.02	0.07	1												
Percent population black	0.27	0.27	-0.33	-0.05	-0.10	-0.13	1											
Population in thousands	0.24	0.22	0.03	-0.13	0.06	0.51	0.21	1										
Income per capita	-0.10	-0.23	0.39	0.14	-0.06	0.18	-0.11	0.23	1									
CDF scorecard ranking	0.24	0.28	-0.36	-0.51	0.03	-0.06	0.09	-0.11	-0.40	1								
CDF Congressional scorecard (CDF) (+better)	-0.20	-0.26	0.35	0.53	-0.06	0.04	-0.13	0.04	0.39	-0.98	1							
GSP in millions	0.22	0.17	0.07	-0.10	0.06	0.53	0.18	0.99	0.30	-0.15	0.09	1						
Change in K-12 Per-pupil exp. 2002-2007	0.11	-0.14	-0.01	0.29	-0.04	-0.09	0.02	-0.14	0.54	-0.28	0.36	-0.08	1					
Number of poor children ages 0-5	0.34	0.32	-0.04	-0.19	0.02	0.55	0.23	0.95	0.08	-0.01	-0.04	0.93	-0.23	1				
Difference b/w state and fed. min wage	-0.10	-0.15	0.23	0.40	-0.02	0.07	-0.20	0.08	0.44	-0.54	0.59	0.13	0.30	0.00	1			
Maximum TANF benefit for family/year.	-0.25	-0.30	0.40	0.16	0.00	0.03	-0.51	0.04	0.50	-0.40	0.45	0.10	0.34	-0.08	0.58	1		
Combined CCDF + HS per-pupil expenditures	0.07	-0.05	-0.19	0.26	0.04	-0.02	-0.05	0.13	-0.07	-0.14	0.18	0.14	0.29	0.11	0.25	0.28	1	
K-12 per-pupil expenditures (thousands)	-0.07	-0.36	0.09	0.37	0.01	-0.11	-0.07	0.03	0.67	-0.53	0.56	0.09	0.74	-0.10	0.47	0.53	0.25	1

Appendix D:
Loadings for the principal components used as Instrumental Variables

	Component number				
Variables	**1**	**2**	**3**	**4**	**5**
Percent women in legislature	0.05	0.15	0.50	-0.14	0.08
Government ideology index (+more liberal)	-0.08	0.28	-0.07	0.03	0.60
Governor is democrat	0.04	-0.15	0.04	0.02	0.78
Percent population Hispanic	0.35	-0.05	0.30	-0.13	0.09
Percent population black	0.11	0.11	-0.64	0.05	0.01
Population in thousands	0.53	0.01	-0.06	0.03	0.00
Income per capita	0.14	-0.01	0.15	0.56	-0.05
CDF scorecard ranking	-0.02	-0.62	0.03	0.06	0.04
CDF Congressional scorecard (+better)	-0.01	0.61	-0.02	-0.01	-0.04
Gross State Product in millions	0.53	0.01	-0.04	0.07	0.01
Changes in k-12 per-pupil expenditures 2002-2007	-0.07	-0.04	-0.14	0.70	0.07
Number of children ages 0-5 in poverty	0.52	0.00	-0.08	-0.08	-0.02
Difference between state and fed. min wage	0.03	0.31	0.11	0.20	-0.02
Maximum TANF benefit for family/year	0.00	0.05	0.42	0.32	-0.08

Appendix E:

Percent variance explained for each principal component

Component	Variance	Difference	Proportion	Cumulative
Component 1	3.43	0.72	0.25	0.25
Component 2	2.71	0.75	0.19	0.44
Component 3	1.97	0.13	0.14	0.58
Component 4	1.84	0.25	0.13	0.71
Component 5	1.59		0.11	0.82

Appendix F:
Pairwise Correlations between parent self-reported inputs and interviewer assessment of parent-child interaction

Preschool			
	Reads books	Sings songs	Positive parenting
Read books	1	-	-
Sings songs	0.22	1	-
Positive parenting	0.23	0.13	1

2 years			
	Reads books	Sings songs	Positive parenting
Read books	1	-	-
Sings songs	0.25	1	-
Positive parenting	0.24	0.15	1

9 months			
	Reads books	Sings songs	Positive parenting
Read books	1	-	-
Sings songs	0.2	1	-
Positive parenting	0.16	0.08	1

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