The Dissertation Committee for Christina Nefeli Caramanis Certifies that this is the approved version of the following Dissertation:

Income, Policy, and Stable Center-Based Child Care: Towards Reducing the Achievement Gap

Committee:

Cynthia Osborne, Supervisor

Robert Crosnoe

Paul von Hippel

Elizabeth Gershoff

Patrick Wong

Income, Policy, and Stable Center-Based Child Care: Towards Reducing the Achievement Gap

by

Christina Nefeli Caramanis

Dissertation

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Doctor of Philosophy

The University of Texas at Austin

August 2020

Acknowledgements

The amount of gratitude I have for my mentors, friends, and family is beyond words. I am extremely grateful for the guidance and mentorship of Cynthia Osborne. Cynthia has been in my corner throughout my time as a graduate student, and her support continues to push me forward. I am grateful for her incredible insight and help becoming part of the Fragile Families team at Princeton and Columbia Universities. I am also thankful for the feedback and mentorship from my dissertation committee members, each of whom has played an integral role in my growth and development as a scholar. I am humbled to have Rob Crosnoe, Paul von Hippel, Liz Gershoff, and Pat Wong on my committee.

I am beyond grateful for my family, friends, and home at the Population Research Center. Thank you to Rachel Donnelly, Jamie Carroll, Carmen Gutierrez, Robert Ressler, Lindsay Bing, Carol Johnston, Diane Coffey, and countless other PRC friends and colleagues who talked data with me, wrote with me, and laughed with me. I would never have made it to this point without you! I am also thankful for many of my wonderful cohort mates at the LBJ School: Abby Lane, Santiago Tellez, Esther Reyes, and Noah Durst.

Finally, I thank my family for their love, support, and encouragement. My parents have been my biggest supporters since the beginning. I am also thankful for by brother, Constantine, who inspires me to be a better version of myself every single day. I am lucky to have had my sweet boy, Darius, alongside me on this journey. Most of all, I have no words for how thankful I am for the person who has stood by me through the good, the bad, and everything in between: Alex Tapper.

Abstract

Income, Policy, and Stable Center-Based Child Care: Towards Reducing the Achievement Gap

Christina Nefeli Caramanis, Ph.D.
The University of Texas at Austin, 2020

Supervisor: Cynthia Osborne

Abstract: Formal child care settings, such as center-based care, are known to increase school readiness, especially among disadvantaged and vulnerable populations. Yet, no research to date has empirically tested the causal link between income and center-based care among economically disadvantaged populations. In my dissertation, I answer this call by applying an instrumental variables strategy to analysis of longitudinal data from the Fragile Families and Child Wellbeing Study (FFCWS) where I leverage state variation in access to state Earned Income Tax Credits as a quasi-experimental instrument for income. My findings, which suggest a causal link between income and the use of center-based child care, represent an important policy-relevant tool by which economic support can foster enhanced early educational experiences that may have important implications for long-term patterns of attainment, achievement, and population health. This study highlights the importance of considering the influence of income support policies beyond their intended scope of promoting financial security and labor market participation.

As part of this dissertation, I also extend our limited knowledge of the long-term academic effects of formal child care enrollment by filling a critical gap in integrated data that concurrently tracks family background, early childhood experiences, and reliable academic outcomes. To do this, I created an original dataset linking the Texas subsample of the FFCWS with Texas administrative school records. Results from my analyses indicate population heterogeneity across indicators of school readiness, grade retention, and math and reading achievement scores. This work highlights the importance of creating integrated data systems to answer questions of both theoretical and practical importance. With a national movement towards expansion of public preschool education that is gaining momentum, understanding the long-term impact of early childhood programs is essential.

Table of Contents

List of Tables

List of Figures

Chapter 1. Introduction

MOTIVATION: THE IMPORTANCE OF EARLY CHILDHOOD

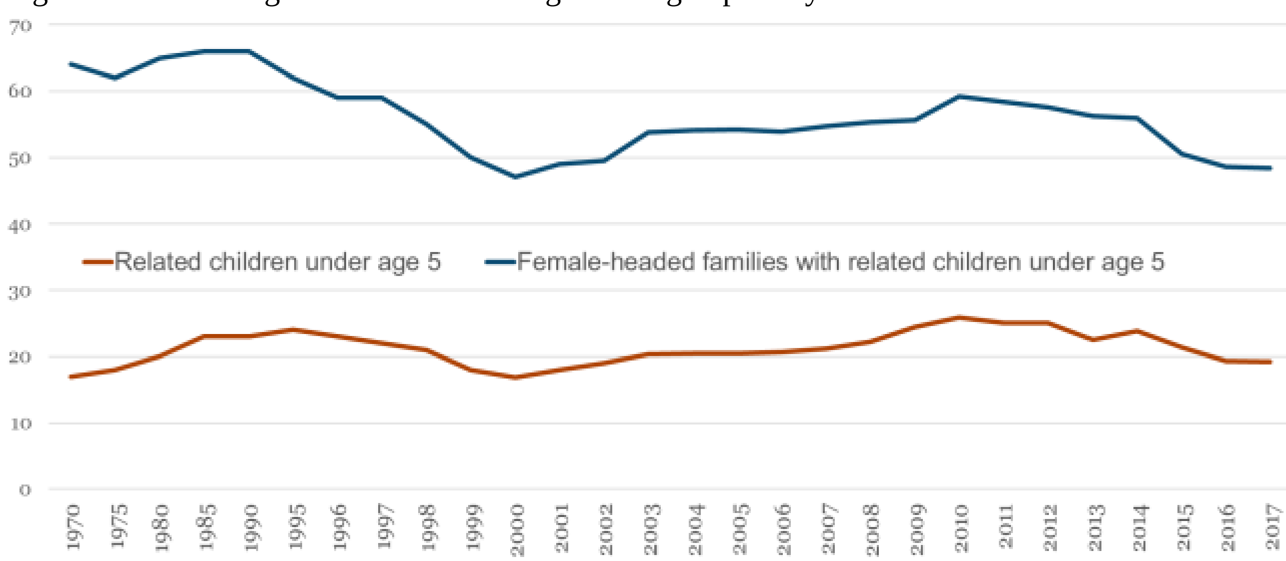
The emotional, social and physical development of young children has a direct effect on their overall development and on the adult they will become (National Academies of Sciences, Engineering, and Medicine [NASEM], 2019). That is why understanding the need to invest in very young children is so important, so as to maximize their future well-being as well as that of society as a whole. The science is clear that the prenatal to 3 period is the most sensitive period of brain development, and it is the time in which our brains are developing the most rapidly (Center on the Developing Child at Harvard University, 2010). At birth, the brain is the only organ that is not fully developed. For instance, newborns' hearts and lungs are just like they are going to be when they become their bigger version, but the brain has to be built. Brains are expecting input from their environment to help them build key systems such as language, vision, or higher orders of function at different periods of time over the first three years. Therefore, providing "good" input is important. The young child's brain is expecting this input from its caregivers to help build a solid foundation and strengthen connections because by the time a child is 3, this period of rapid growth slows down dramatically. Consequently, the brain's capacity for change decreases with age (Blair & Raver, 2015; National Scientific Council on the Developing Child, 2012). The prenatal to age 3 period, therefore, lays the foundation for later advantage or disadvantage, thus the more adverse experiences in childhood, the greater the likelihood of developmental difficulties and other problems. On the flip side, early intervention can prevent the consequences of early adversity. Research shows that, although later interventions may lead to some remediation, earlier interventions are more likely to be successful, and will almost certainly be more cost effective (National Scientific Council on the Developing Child [NSCDC], 2020).

The research is clear, then, on what children need to thrive. If children do not get safe, stimulating, loving, caring environments in their earliest years, it impairs the development of their brain, and it puts strain on their physiological system that, over time, can lead to poorer health behaviors and other negative outcomes (National Scientific Council on the Developing Child, 2012). Thus, if optimal conditions are put in place during these earliest years, this lays the foundation for all future learning, behavior, and health. Furthermore, in addition to making the wellbeing of an individual better off over the course of their life, from a societal perspective, it is a lot less expensive, and a lot better for society as a whole if families have the tools and resources necessary to "get it right" in the earliest years, thereby leading to long-term payoffs over the life course (Knudsen, Heckman, Cameron, & Shonkoff, 2006).

In terms of a child's early ecology, economic disadvantage can be particularly harmful to healthy child development (Currie & Almond, 2011; Johnson, Riis, & Noble, 2016; Noble et al., 2015). Affecting nearly one in five children under age 5 (NASEM, 2019), poverty during the first few years of life can lead to a range of negative outcomes, such as lower educational achievement and attainment (Duncan et al., 2007), which can be extremely damaging and lead to persistent disadvantage throughout one's life (Duncan, Magnuson, & Votruba-Drzal, 2014). In addition to being a topic of great importance in empirical studies and literature, childhood poverty is something we have long paid attention to in the media and beyond. And with this scrutiny, we have long known that excessive or prolonged stress that comes hand-in-hand with economic disadvantage can be toxic to the developing brain. So what, then, have we effectively done about it?

The answer is, not much. As illustrated in Figure 1.1, rates of early childhood poverty have largely oscillated between 21 and 26 percent over the past 35 years (U.S. Census Bureau, 2017), and recent literature reports either static or, in some cases, higher rates of poverty among children up to the age of 5 today than in 1968 (Pac, Nam, Waldfogel, & Wimer, 2017). And the situation is far worse for female-headed families where upwards of one in two children are deemed poor (U.S. Census Bureau, 2017). In the U.S., we use an absolute measure of poverty, which compares households based on a set income level that has only changed slightly to account for inflation since its creation in 1965. 100% of the Federal Poverty Level (FPL) is, for instance, defined as around $20,200 for a family of three with at least on dependent child under the age of 18, and about $17,300 for a single parent with one child (Semega, Kollar, Creamer, & Mohanty, 2019).

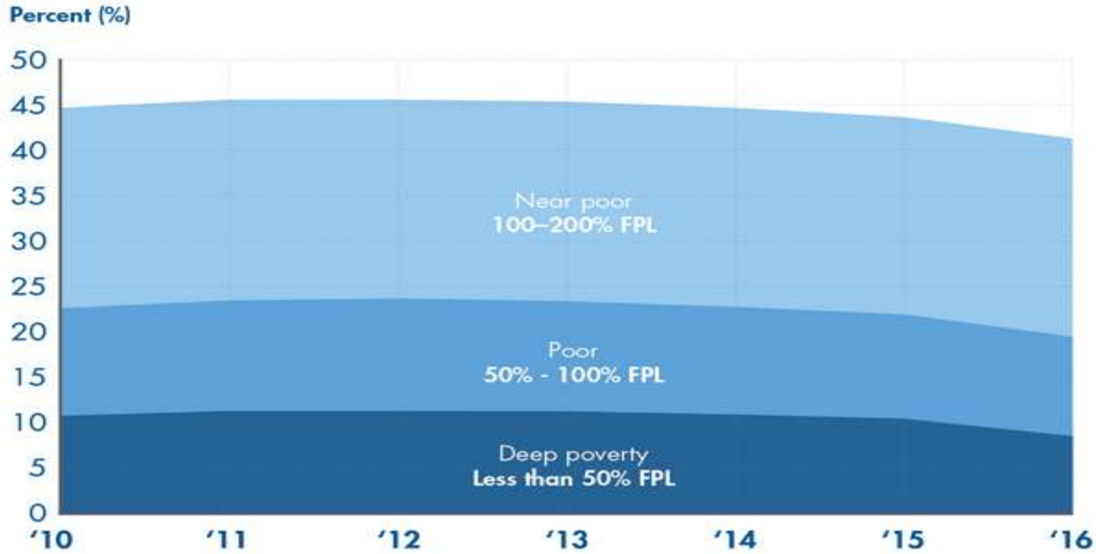
Figure 1.1: Percentage of children under age 5 living in poverty.



Source: US Census Bureau, 2017

Figure 1.2 shows that in addition to 20% of our children growing up in poverty, another 20-25% qualify as low income. This is defined as family income less than 200% of the Federal Poverty Level. That means that nearly half of U.S. children are tasked with development under less than ideal circumstances to put it mildly. And again, this is far worse for children in single-parent households.

Figure 1.2: Children living in low-income and poor families, 2010-2016.

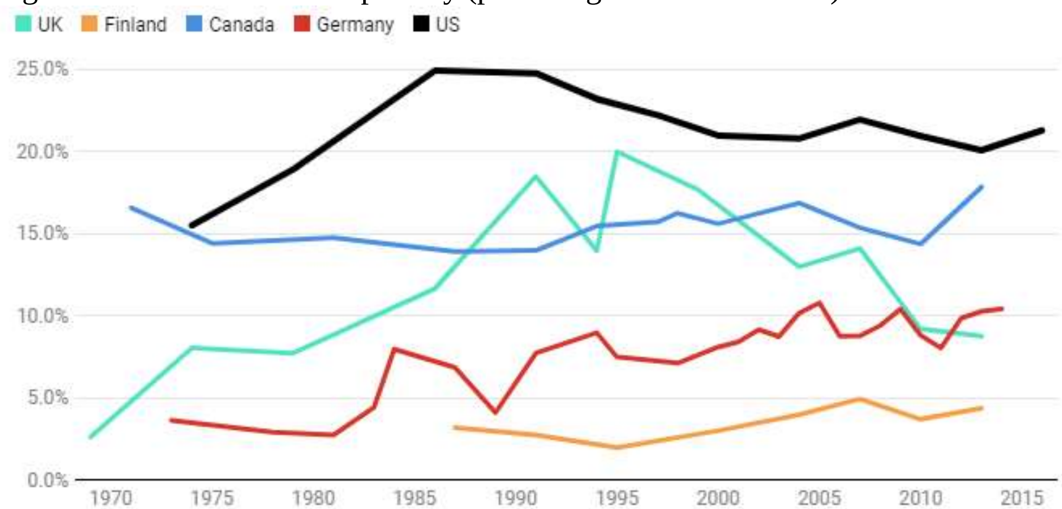


Source: National Center for Children in Poverty

Although considerably higher than in many other industrialized nations, persistent poverty is not unique to the U.S., and it is not something that will go away overnight. It is clear that we are far from eradicating this pernicious problem across the globe. It is necessary, therefore, that we look at what we know about our current anti-poverty policies and, importantly, where we have yet to look for answers. We need to think outside the box about mechanisms that can counteract the negative correlates of early life disadvantage, and, perhaps, how we might potentially work with what we have to achieve greater equity.

To reiterate, we know that early intervention can prevent the consequences of early adversity. When a young child is protected by supportive relationships with adults, she learns how to adapt to everyday challenges and her stress response system returns to baseline (National Scientific Council on the Developing Child, 2012). It is worth noting, however, that although poverty rates can be measured in relative terms—less than 50% of the national median income, as we see in Figure 1.3 below—in comparison to other OECD countries, the U.S. context is exacerbated, and perhaps even more out of line with the rest of the developed world than portrayed in relative comparisons, by the fact that in addition to no national healthcare, the U.S. offers no federally funded subsidies for parental leave (so mothers, and especially single mothers, often have little to no choice about going back to work after the birth of their child), and, importantly, no universally available free or subsidized early childhood care and education before kindergarten at age 5. As a result, in comparing U.S. child poverty to that of other developed nations, like is not quite being compared to like. [Note: If relative poverty is set at lower than 60% of median income, the U.S. percentage goes from 23.1 in 2015 to 31.1.]

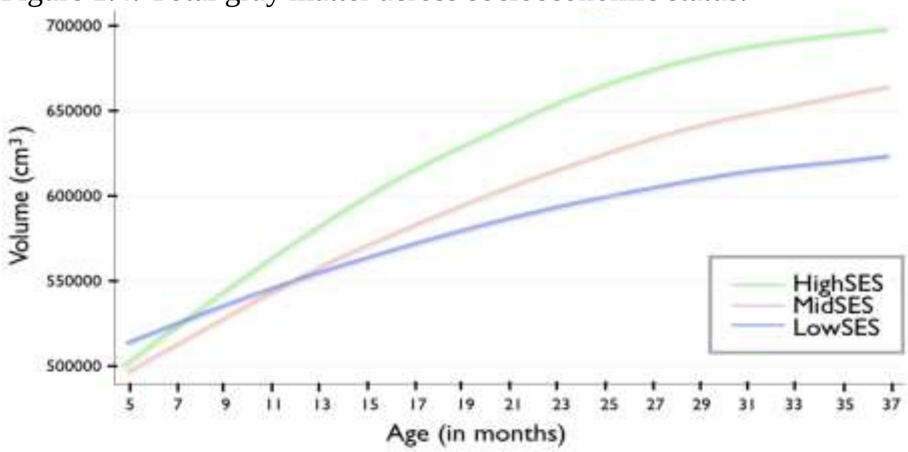
Figure 1.3: Relative income poverty (percentage of children 0-17).



Source: Luxembourg Income Study

Nevertheless, the negative correlates of economic disadvantage are universal. Figure 1.4 shows that it really is a child's environment that shapes his or her brain's development. Gray matter, a type of brain tissue that contains neural cell bodies, dendrites, and synapses that support information processing and execution of actions, is what neuroscientists focus on to indicate healthy brain development in young children (Hanson et al., 2013). Children start off with similar levels of gray matter, regardless of their parents' socioeconomic status. Over the course of the first three years of life, however, children in higher SES environments show stronger development of gray matter in their prefrontal cortex, likely because they are getting more stimulation, are exposed to lower levels of stress, and have more consistent resources and stability in their environment. Children with middle and lower levels of income, on the other hand, do not receive the same level of stimulation on average, and therefore, by the time they are 3 years old, neuroimaging reveals weaker gray matter development than is seen in the brain scans of their wealthier counterparts who are raised in higher resource environments.

Figure 1.4: Total gray matter across socioeconomic status.

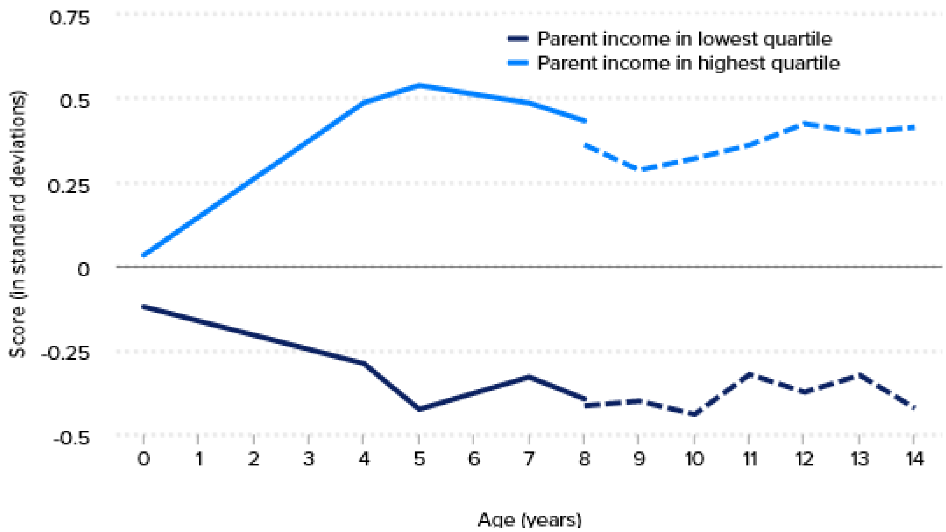


Source: Hanson et al., (2013) PLOS ONE

This is important because it sets the stage for later advantage or disadvantage. In the U.S., studies find that the achievement gap representative of socioeconomic stratification is largely set by the age of 5 (von Hippel, Workman, & Downey, 2018). Research suggests that achievement gaps take root in early life and are, therefore, highly susceptible to environmental conditions surrounding the early childhood home and care settings. Measures of school readiness are important because they are powerful predictors of later school success. Thus, in addition to being difficult to close, achievement gaps, first measured in kindergarten, are likely to persist as a child advances through school (Crosnoe et al., 2016; Duncan et al., 2007; Friedman-Krauss, Barnett, & Nores, 2016). Crosnoe and colleagues (2016) summarize the argument for growth in the achievement gap: “children from low-income families enter the K-12 educational system with less developed academic skills that are then acted upon by formal and informal processes of schooling (e.g., ability grouping, teacher expectations) to create larger end-of-school disparities that undermine their ultimate socioeconomic attainment” (p. 2). Socioeconomic disparities in school readiness would thus perpetuate socioeconomic inequality across generations. We know that poor academic achievement is a primary pathway to lasting adversity, so with low-income children entering school up to a full year behind their wealthier counterparts, it is clear that we must act early. In short, gaps that appear in kindergarten—and which are hence (at least in part) the result of investments in very young children’s development—tend to persist throughout children’s lives. Thus, if we want to reap the enormous potential benefits of closing income-based achievement gaps, we need to equalize resources available to young children even before they begin traditional pre-K and elementary school.

This includes investing in quality early child care and early childhood development activities. Figure 1.5 shows that measures of children’s cognitive skills begin diverging reliably across income classes even before ages 3 and 4. This leaves considerable room for even earlier childhood interventions than pre-kindergarten to help close achievement gaps.

Figure 1.5: IQ/test scores in standard deviations, by parent income quartile.



Source: EPI adaptation from Council of Economic Advisers (2014)

As noted earlier, what children need to thrive is not particularly complicated. Children need safe, stable, loving, caring interactions with their caregivers, and *that* is what leads to healthy brain development. This does not, however mean that it is easy, and for some families, it is quite complex. For instance, when parents have to work several different jobs to make ends meet, or there is maternal depression, substance abuse, or other hardships that can make it difficult for parents to provide safe, loving, and stimulating environments for their children, this is when infants and toddlers face barriers to optimal early development. What parents need are the resources along with the skills, health, and social connections that create those conditions in which their children can thrive.

Extensive research shows that policies can in fact help to create these conditions for families, whereby families are exposed to lower levels of stress and have greater stability in their resources so that children can thrive in safer and more developmentally appropriate environments. What, then, are the specific mechanisms through which we can disrupt the negative correlates of economic disadvantage in early life?

THE PRESENT STUDY

Formal early childhood education and care, such as center-based care, can help mitigate many of the negative correlates of early childhood disadvantage, but it is out of reach for many of our most vulnerable children. In particular, stable exposure to formal early care settings, such as a center-based or other educational preschool, has been shown to boost school readiness and to reduce the achievement gap by improving short-term cognitive and academic outcomes (Magnuson & Duncan, 2016). There is, however, a critical gap in the literature on what we know about how income might influence exposure to center-based child care among low-income families and, in turn, how various early childhood care configurations may affect different groups of children over time.

With roughly 73% of children ages 3 to 5 experiencing some form of regular non-parental care before entering kindergarten (Corcoran & Steinley, 2017), most parents are challenged with finding and maintaining accessible child care that aligns with their preferences, family, employment, and economic constraints. For low-income and single parents with limited resources, the need for affordable child care often results in more informal home-based care settings that do not typically promote early learning and development (Dowsett, Huston, Imes, & Gennetian, 2008). Moreover, as family and employment circumstances change, lower-income parents often make frequent changes in providers or rely on multiple, concurrent arrangements (Pilarz, 2018; Pilarz & Hill, 2014). The association between child care instability and lower levels of academic success (Ansari & Winsler, 2013) is an alarming pattern.

From a policy standpoint, there are various ways to affect income that might enable poor families to access stable center-based care. Income-support policies are designed to increase household income by encouraging parents to work and supplement their take-home pay through direct cash transfers, such as the Earned Income Tax Credit (EITC), or by alleviating cost burdens related to work, such as subsidized child care. To my knowledge, no studies to date have examined the extent to which access to additional sources of direct income such as the EITC might contribute to increased enrollment in stable center-based care among children from diverse low-income families.

With a national movement towards expansion of preschool education that is gaining momentum (Duncan & Magnuson, 2013), it is necessary to understand how access to supplemental income and policy support might positively influence rates of stable exposure to center-based care and extend our current understanding of how dimensions of child care influence children's short- and long-term academic success. Despite substantial evidence linking enriched early care settings to short-term academic outcomes, studies of long-term academic effects are limited by a dearth of studies with long-term follow-ups (Yoshikawa, Weiland, & Brooks-Gunn, 2016). Beyond a general consensus that a handful of programs implemented several decades ago had important long-term effects, studies to date have not illuminated the specific mechanisms through which these programs achieved their positive results (Magnuson & Duncan, 2016). Moreover, we still lack a comprehensive understanding of how early care environments shape academic achievement across various child and family characteristics that are associated with academic achievement and attainment.

Thus, the aims of this dissertation are:

- Aim 1: To assess the causal role of income on the use of stable center-based care.
- Aim 2: To test the association between stable center-based care and children's short- and long-term academic success and examine differential treatment effects across baseline child and family characteristics.

In addressing these aims, this dissertation is well-positioned to address important gaps in the literature by focusing on outcomes relevant to child care and education policy, while also exploring policy-relevant avenues for increasing stable exposure to center-based care among children from diverse low-income working families. This is particularly important in light of the rise in non-parental child care coupled with persistent rates of child poverty in the U.S. Despite a well-documented association between income and academic success and attainment, studies have not considered the role of income precipitated through income-support policies in shaping parental decisions around child care, and the extent to which stable exposure to center-based care may matter more for children from different sociodemographic backgrounds. By applying advanced statistical techniques to longitudinal data from the Fragile Families and Child Wellbeing Study (FFCWS), this dissertation examines heterogeneity in response to fluctuations in income, access to work and income supporting policies, and child care exposure profiles. This dissertation contributes to our understanding of income, economic policies, patterns of child care exposure, and academic linkages.

In this dissertation, I draw attention to how patterns of child care enrollment and academic attainment vary for one specific subpopulation of children: low-income children. Although a multitude of factors can impede healthy development, it is important that we narrow in on children growing up in diverse low-income families, as these children are the children at greatest risk of less optimal development (NASEM, 2019) and high-quality care can support their positive development (Yoshikawa et al., 2013). From an economic perspective, low-income families are less able, due to income constraints, to purchase important developmental inputs that can help keep a child’s mind and body healthy (e.g., high quality educational settings from early childhood through adolescence, and safe environmental settings) (Duncan & Magnuson, 2013).

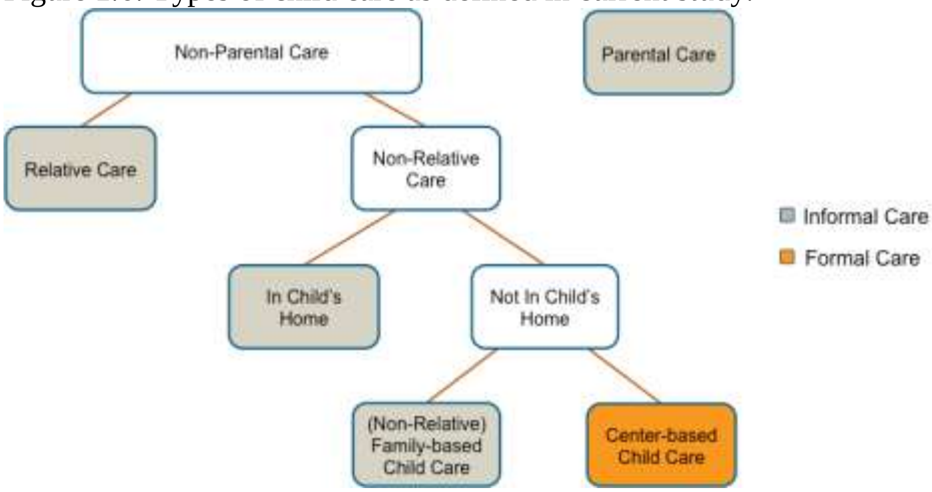
U.S. Policy as a Lever to Encourage Use of Center-Based Child Care

In the U.S., we have a number of policies aimed at getting children into developmentally appropriate early environments such as center-based child care. We have child care subsidies that are provided to low-income families through a federal block grant program: The Child Care and Development Fund (CCDF). However, funding for subsidized child care is not sufficient to serve all families who face financial barriers. Unlike universal means-tested programs in which eligible recipients who apply are guaranteed receipt, the subsidy program is a block grant administered at the state level. It is not an entitlement, so not all eligible applicants receive a subsidy (Derrick-Mills, 2009). Estimates of the proportion of eligible children who are served by the program vary between 15-20 percent (Shanks & Danziger, 2010). Early Head Start, the downward extension of the Head Start program for infants and toddlers, provides high quality center-based care for just over 350 thousand children each year (Head Start Program Facts: Fiscal Year 2019), but serves only a small fraction of all eligible children. A number of states have implemented public pre-K, but this too is not universal, and is typically only offered in the year before kindergarten.

Types of Child Care in the U.S.

As illustrated in Figure 1.6, children can be in either non-parental or parental care. In terms of non-parental care, children can be in the care of a relative or non-relative, in the child's home or outside in a home-based (or family-based) setting or a child care center. Informal child care arrangements are defined in this dissertation as parent and family-based settings including non-relative home-based child care, and being cared for by a non-parent in the family's home. Formal child care arrangements are defined as the set of all early childhood education and care services to children 0-5 (not yet in kindergarten) provided by an organization in a single location, including Early Head Start, preschools in public schools, private nursery schools, day care centers, and other types of early childhood education and care. For the purposes of this dissertation, I use formal child care and center-based child care interchangeably.

Figure 1.6: Types of child care as defined in current study.



How Does Center-Based Child Care Mitigate Poverty?

Compared to family-based and other informal child care settings (which I refer to as family child care), child care centers are characterized by multiple caregivers, they are more structured, include developmentally appropriate and educationally-oriented activities and curriculum, have more space, toys, and educational activities, and, importantly, are comprised of caregivers with more training and education (Dowsett et al., 2008). As a result, center-based care is associated with better cognitive and pre-academic skills relative to comparably evaluated home-based child care (Crosnoe, Pickett, Smith, & Cavanagh, 2014; Dowsett et al., 2008).

Enhanced early childhood experiences (e.g., placement in stable, formal center-based or other educational preschool care) have the unique potential to reduce the socioeconomic gap in educational attainment by preparing low-income children for school entry (Crosnoe et al., 2016). Children who succeed academically in early and middle childhood are more likely to graduate high school, attend college, and earn higher wages (Crosnoe et al., 2016; Duncan et al., 2007;

Ensminger & Slusarcick, 1992; Friedman-Krauss et al., 2016). Sustained accumulation of human capital that starts in early childhood settings and continues throughout the educational experience is, therefore, likely to translate into substantially better life outcomes and overall success throughout the life course. Early childhood education interventions such as placement in formal center-based child care can thus improve children’s development and act as a protective factor against the future onset of adult disease and disability.

Although some studies have found mixed results in terms of emotional development and self-regulation, they find these benefits do extend to poor and low-income children, who tend to reap the largest benefits from center-based child care overall (Loeb et al., 2007). Furthermore, especially for lower-income children, more exposure to stable center-based care leads to better results (Barnett, Jung, Youn, & Frede, 2013). Studies have also documented savings and gains for individuals and society ranging from increases in maternal employment and income, better jobs, and all around savings from reductions in grade retention and remedial education, as well as overall societal earnings gains and improvement in health outcomes, among others (Bivens et al., 2016).

Determining the effects of child care on children's development, however, is challenging because there is limited evidence from randomized trials, and there is an overall dearth of longitudinal data that are able to accurately and concurrently track family background, early childhood experiences and reliable academic, health, and workforce outcomes. Given this latter point, in the final chapter of my dissertation, I link the Texas subsample of the Fragile Families and Child Wellbeing Study to their administrative records housed in one of the country’s best State Longitudinal Data Systems in Texas to examine over 20 years of linked longitudinal Data.

Child Care Across Household Types

Despite the need for additional research, it is abundantly clear that as a society, one of the best investments we can make is to optimize the early years of children's lives to ensure their future success. However, many of our most vulnerable children are not benefitting from exposure to formal center-based child care settings.

For the most part, children ages zero to 3 are most often placed in informal non-parental child care arrangements, with the share of children exposed to center-based care increasing with age. Looking at types of care across income quintiles, we see that on average, poor and low-income children experience lower rates of center-based care compared to all families across all ages (Harding & Paulsell, 2018). Research reveals that children in low-income families are more likely to end up in informal family or other non-parental home-based care settings, which have been shown to result in lower levels of school readiness (Duncan et al., 2014; Feller, Grindal, Miratrix, & Page, 2016) and subsequent academic achievement and attainment (Duncan et al., 2007).

Examining reasons why more low-income children are not exposed to formal center-based child care, one theme is abundantly clear: child care is expensive! For children ages birth to 5, the proportion attending any type of non-parental child care and the proportion attending center-based child care both increase with income, likely because of the high cost of child care, particularly center-based child care. In fact, child care costs are one of the most significant expenses for low-income families, with all types of care costing most for younger children, and the cost of center-based care far exceeding the cost of any other informal home-based type of care (Bivens et al., 2016).

Poor and low-income families, therefore, end up burdened with having to direct a higher portion of their income towards child care costs, which can be particularly taxing for those making minimum wage. For instance, Gould and Cooke (2015) report that for a parent working 40 hours per week, 52 weeks per year making minimum wage in 2014, child care can cost 30-80% of her annual income for a 4-yr-old, and 32 to over 100% of her income for infant care across U.S. states. The question, then, is: given the lack of programmatic or policy infrastructure specifically directed at getting our most vulnerable children into developmentally appropriate child care arrangements, how do parents choose early care arrangements for their children?

Child care instability, defined here as changes in a child care provider, is also an important mediator of academic success affected by a family's economic status. Research finds poverty to be associated with a higher likelihood of experiencing child care instability (Adams & Rohacek, 2010; Duncan & Magnuson, 2013; Sandstrom & Huerta, 2013), which, explored in greater detail throughout the remainder of this dissertation, may be another policy-relevant mechanism through which poverty undermines children's development and leads to socioeconomic stratification (Chaudry, 2004; Loeb, Fuller, Kagan, & Carrol, 2004).

Although multiple and concurrent child care arrangements are common for a substantial number of children in the U.S., the risk of child care multiplicity increases significantly among low-income families (Sandstrom & Huerta, 2013). Low-income families find it more difficult than their higher-income counterparts to access child care and maintain consistent child care arrangements in a single-provider setting (Chaudry, 2004; Laughlin, 2013; London, Scott, Edin, & Hunter, 2004). Using U.S. census data, Laughlin (2013) finds that nearly 26 percent of children ages zero to 5 who live in households below the federal poverty threshold and whose mothers work, experience multiple child care arrangements prior to age five, as compared to 20 percent of all children (Morrissey, 2010). Multiple child care changes and arrangements are related to factors such as fluctuating incomes, parental nonstandard work hours, employment instability, and limited access to child care subsidies (Chaudry, 2004; Danziger, Ananat, & Browning, 2004; Enchautegui, Johnson, & Gelatt, 2015; Han, 2004; Scott, London, & Hurst, 2005). Thus, it is important to understand sources of additional mechanisms through which poverty may undermine the healthy development of children beyond demographic risks.

Child care instability, particularly for children in poverty, can often be attributed to instability in other domains of family life characteristic of low-income households (Sandstrom & Huerta, 2013). Examples of these characteristics include disruptions in parental employment and income, housing arrangements, or family structure (Bratsch-Hines, Mokrova, & Vernon-Feagans, 2017; Loeb et al., 2004; Sandstrom & Huerta, 2013). Common amongst low-income households, instability in employment and income, for example, can often result in children "drifting" between formal child care when parents find temporary jobs and home care when parents lose those jobs (Scott & Abelson, 2013). Child care instability may lead to instability in these other domains, thereby compounding the harmful effects on child development and socioeconomic stratification (Bratsch-Hines et al., 2013; Sandstrom & Huerta, 2013).

Theoretical Perspectives

Child Care Enrollment

In chapter 2, I explore, both theoretically and empirically, mechanisms by which parents may enroll their child in certain child care arrangements over others. Although quite difficult to systematically quantify, there are two overarching schools of thought as to why parents enroll their children in certain child care types over others: Income and Cultural preferences/values.

Looking first to income as the biggest barrier to center-based child care, scholars note that working parents want to know that their children are being taken care of and learning in safe and healthy environments (Becker, 1981; Becker & Tomes, 1986). The Family Investment and

Resource Theory therefore posits that, given the resources, parents will choose the best early childhood environment for their children, such as center-based care. However, to date, we do not know how an increase in income might shape decisions around child care use of low-income families, in particular.

Other scholars, however, look to culture and sociodemographic characteristics as an explanation for child care selection (Crosnoe et al., 2016; Kornrich & Furstenberg, 2013; Lareau, 2002). The accommodations framework and other sociocultural theories of spending as a parental investment posit that selection into child care is based on a number of often competing factors such as race/ethnicity, family structure, number of dependents in the household, child age and gender, maternal educational attainment, maternal depression, maternal work schedule, and receipt of welfare, in addition to household income (Crosnoe et al., 2016).

The problem with cultural explanations for child care preferences, however, is that it is difficult to quantify the impact of culture and background, and likewise difficult to intervene on such characteristics through policy. Moreover, by saying child care enrollment is based on immutable family characteristics, the onus of early exposure to center-based child care is placed squarely on the shoulders of parents as family "preference."

In this dissertation, therefore, the goal of the first empirical chapter was to explicitly quantify the contribution of income as a key factor in explaining why disadvantaged children are not benefitting from formal center-based care, even through we know that high-quality early education can be a game-changer for the children and families who need the most support. I argue that this an essential line of inquiry, not only because it is more feasible and actionable than cultural perspectives, but also because we need to start looking outside the box for solutions that can make a difference in the lives of our most vulnerable children.

Looking then to causality in support of the theoretical claim that, given the resources, parents will choose formal child care options for their children, what we find is that there are a number of empirical challenges that must also be addressed. It is difficult to isolate the influence of income because of the endogeneity of household income. In other words, unobserved determinants of income, such as state-level policies or socioeconomic status, which includes educational attainment, may also be influencing child care selection. This omitted variables problem can produce biased results in the relationship between income and child care enrollment patterns. To address this, I leverage an Instrumental Variables design coupled with a robust set of controls to identify exogenous variation in household income and estimate the unbiased local average treatment effect of income on exposure to child care arrangements.

An instrument is something correlated with the causal variable of interest (income in this case) but uncorrelated with any other determinants of the dependent variable (child care enrollment patterns). Studies often use random assignment to treatment and control situations as an instrument, but variables that include random variation outside of experimental contexts can also be used to simulate quasi-experimental conditions. This instrumental variable can then be used to solve omitted variables bias problems. I take advantage of natural policy variation in the Earned Income Tax Credit (EITC) as an instrument for exogenous income.

Created in the 1970s, the EITC is the most important anti-poverty program in the U.S. It is a refundable tax credit that aims to incentivize labor-force attachment among low-income parents. It is the refundable nature of the credit that makes it so effective. What this means is that, as opposed to other tax breaks such as the Child Care Tax Credit that only lessens the tax burden for those who make enough to owe taxes, families can benefit from the EITC even when they have no tax liability (Nichols & Rothstein, 2015).

As illustrated in Figure 1.7, the structure of the credit is a trapezoid, whereby benefits increase along with income, plateau, and then decrease as earnings continue to rise. Single mothers of two and three or more children are eligible for the maximum benefit at about $14,290 of income. For a mother with three or more children the maximum benefit would be just under $6,500, and for a mother of two it would be just over $5,700. A single mother of one, on the other hand, would be eligible for a maximum benefit of nearly $3,500 at around $10,180 of net income. This represents a large chunk of money for low-income families.

Figure 1.7: The phase-in and phase-out of the EITC (credit amount by marital status and number of children.

Source: Amir El-Sibaie, “2019 Tax Brackets,” Tax Foundation, Nov. 28, 2018.

As exemplified by this structure, the EITC was created to encourage work and labor force attachment to low-paying jobs. About 86% of eligible families actually claim the credit (Shanks & Danziger, 2010), which is considered quite high in terms of participation rates. Finally, another very important element of the credit, the part that introduces random variation, is the fact that many states also implement their own EITCs. State EITCs are up to the discretion of individual states, and typically represent a percentage of the Federal EITC. Because State EITCs introduce between and within state variation in terms of timing and generosity, the EITC has been used as an instrument for income in many studies trying to isolate the exogenous influence of income (e.g., Bastian & Michelmore, 2016; Dahl & Lochner, 2012).

To illustrate the applicability of state EITC as an instrument in this study, looking at the 15 states included in the Fragile Families data during the study period (Table 1.1), we can see between state variation illustrated by the fact that some states have it, and some do not, and we can see within state variation when a state first introduces the credit or changes the rate from one year to the next. For example, a mother of two in Texas, a state with no EITC beyond the federal credit, would be eligible for a maximum total benefit of about $5,700 in any year between 1998 and 2003. A mother of two in New York in 1998, however, would receive the same $5,700 along with an additional 20% of the federal credit. In 2003, when New York changed its rate to 30%, this maximum benefit would total nearly $2000 more than the federal credit alone—a difference that can mean a lot in the lives of most low-income parents.[1]

Table 1.1. State EITC benefits as a proportion of federal EITC in 15 FFCWS states.

	1998	1999	2000	2001	2002	2003
California	--	--	--	--	--	--
Florida	--	--	--	--	--	--
Michigan	--	--	--	--	--	--
Ohio	--	--	--	--	--	--
Pennsylvania	--	--	--	--	--	--
Tennessee	--	--	--	--	--	--
Texas	--	--	--	--	--	--
Virginia	--	--	--	--	--	--
Illinois	--	--	**0.05**	0.05	0.05	0.05
Indiana	--	--	--	--	--	**0.06**
Maryland	0.10	0.10	**0.15**	**0.16**	0.16	**0.18**
Massachusetts	0.10	0.10	0.10	**0.15**	0.15	0.15
New Jersey	--	--	**0.10**	**0.15**	**0.18**	**0.20**
New York	0.20	0.20	**0.23**	**0.25**	**0.28**	**0.30**
Wisconsin (1 child)	0.04	0.04	0.04	0.04	0.04	0.04
Wisconsin (2 children)	0.14	0.14	0.14	0.14	0.14	0.14
Wisconsin (3 children)	0.43	0.43	0.43	0.43	0.43	0.43

Source: Adapted from Jones and Michelmore (2016).

[1] It should be noted that these amounts are not quite exact, as the benefit amount is indexed annually for inflation, but this doesn't yield a huge monetary difference, and these examples are only meant as a general illustration.

Differential Effect of Child Care Enrollment

In chapter 3 I explore the differential effects of various child care enrollment patterns in Texas. Research consistently finds that greater socioeconomic and sociodemographic risk in early childhood is negatively related to children's academic achievement and competencies. Similarly, the relationship between academic achievement and child care type and stability likely varies across early childhood ecologies that differ in terms of socioeconomic and sociodemographic risk at both absolute (i.e., additive or cumulative number of risk factors) and configural (i.e., groupings of co-occurring risk factors) levels. Recent scholarship has thus demonstrated a growing interest in differential treatment analysis to discover which subgroups of children might benefit most from targeted interventions (e.g., Cooper & Lanza, 2014; Duncan & Magnuson, 2013). However, the extent to which stable center-based care differentially benefits children based on sociodemographic groupings of risk remains largely unknown.

Extensive research finds that socioeconomic factors independently predict both selection into various child care types and measures of academic achievement throughout the school years. Many families cannot afford to pay for more expensive formal care settings and do not receive public assistance to subsidize the cost. Studying a representative sample of 6,250 children born in the U.S. in 2001, Crosnoe et al. (2016) found that parents who reported needing reasonably priced child care options were less likely to choose center-based care (exclusive of Head Start). They further found that, compared to their higher-income counterparts, low-income families (<185% FPL) were significantly less likely to enroll a child in some form of center-based preschool at age 4.

Other disadvantaging sociodemographic factors, beyond economic indices of risk, can also predispose children to informal care settings. Risk factors involving family composition (Crosnoe et al., 2014), language (Yoshikawa et al., 2016), welfare receipt (Cooper & Lanza, 2014), maternal immigrant status (Cooper & Lanza, 2014), depression (Crosnoe et al., 2014), education, employment status (Coley et al., 2014; Crosnoe et al., 2016) and teen motherhood, as well as the child's race/ethnicity, early literacy and need for special education (Yoshikawa et al., 2016), can all serve as barriers to entry into formal child care arrangements. Often children from such disadvantaged backgrounds stand to benefit most from the educational inputs provided in formal child care settings, which may be lacking at home. Thus, selection into various configurations of child care type and stability can serve to further widen the gap between children who are exposed to the cognitive benefits of formal child care settings and those who are not.

A small yet growing body of literature finds that the direct effect of child care type and stability on academic outcomes can likewise vary across socioeconomic and sociodemographic lines. The theory of resource substitution posits that the beneficial effect of stable center-based care may be greater for children from more disadvantaged backgrounds with fewer alternative resources (Andersson, 2016; Magnuson & Duncan, 2016; Ross & Mirowsky, 2006). Accordingly, much of the extant literature on heterogeneity of outcomes related to early care focuses on children from low-income families, finding that children from the most economically disadvantaged families stand to gain more from formal care settings that promote academic preparation than their more advantaged peers (Coley, Votruba-Drzal, Collins, & Cook, 2016; Johnson, 2017).

Other sociodemographic risk factors such as low parental education and minority race/ethnicity have also been found to differentially predispose certain subgroups of children to increased benefits of formal child care settings. Currie and Almond (2011) find that in addition to low socioeconomic backgrounds, children of parents with low levels of education benefit most from formal child care attendance. Evaluating the effect of Head Start on grade repetition, among other things, Currie and Thomas (1995) found that the probability of grade repetition was significantly reduced for white children, but had no effect for black children. More recent evaluations of universal pre-kindergarten programs in Tulsa, OK and Boston, MA demonstrated larger marginal effects in short-term reading, math, and language skills for Asian, Black, and Hispanic children, as well as English language learners (Yoshikawa et al., 2016). A separate impact evaluation of Tulsa's pre-kindergarten program in Oklahoma found that the program was more effective for children whose parents were born in Mexico (Gormley and Gayer 2005). In terms of disparity in the persistence of outcomes, Currie and Thomas (1995) also found that, while the Head Start program evaluation revealed significant gains in test scores among both white and black children, gains among black children rapidly diminished. Thus, in terms of additional sociodemographic risk factors, the theory of resource substitution assumes that children with the greatest number of risk factors stand to benefit most from stable center-based care.

On the other hand, the concept of cumulative advantage holds that the effect of accumulating resources is multiplicative, such that child outcomes are based on the resources they bring to the table prior to the measured outcome of interest. In other words, it may be that children who enter formal care with more resources—either because of repeated exposure to early childhood education or because their parents have the capability to invest more time and/or money—stand to benefit most from formal options. The expectation of this "skill-begets-skill" model, therefore, would be that children with the least number of risk factors, as well as children with stable exposure to formal care, are in a position to reap the greatest gains from early childhood education (Cunha, Heckman, Lochner, & Masterov, 2006). However, by not taking a theoretical stance on the differential impact of negative environmental stimuli (e.g., informal child care settings) into account, both the cumulative advantage and resource substitution models may underestimate the aggregate effects of early care settings on academic achievement. Furthermore, very little is known about how particular *groupings* or configurations of risk (as opposed to an additive tally) may influence a child's academic trajectory.

A third, and rather underexplored, possibility is that supported by the differential susceptibility model (Belsky & Pluess, 2009), which posits that children vary in the extent to which they are affected by their early care environments. Under the assumptions of this model, the dynamic nature of risk factors at play interact in various ways, thereby exerting different levels of influence, depending on the particular configuration of risk factors that define a child's early ecology. Taking a sociodemographic background characterized by high risk, for instance, the differential susceptibility framework accounts for both the benefits of positive environmental conditions (e.g., steeper increases in academic achievement stemming from formal child care), as well as adverse effects of negative environmental conditions (e.g., lower academic achievement influenced by informal child care). The hypotheses underlying the present study borrow elements from each of these theories to explore population heterogeneity in measures of academic achievement associated with child care type and stability over time.

Overview of Dissertation

My dissertation project uses advanced quantitative methods to uncover implications of income-support policies for early childhood education and academic achievement. Although there is extensive theoretical and empirical work detailing the linear effect of various policies on their intended outcomes, there is a dearth of theoretically informed empirical research on how such policies may affect other proximate or intermediary early childhood experiences. For example, how might a given income-support policy influence exposure to early childhood educational contexts? In turn, what are the long-term consequences of these intermediary contexts? I address these gaps through rigorous research design and by applying quasi-experimental and other advanced analytic methods to longitudinal data—including an original dataset where I link longitudinal survey and administrative data—to examine non-linear or less evident ways in which micro- (i.e., individual) and macro- (i.e., policy) level contexts intersect, and the social, political and economic consequences therein.

In chapter 2, I investigate how policy-induced changes in income can shape exposure to child care arrangements for low-income families. Formal child care settings, such as center-based child care, are known to increase school readiness, especially among disadvantaged populations. Yet, no research to date has empirically tested the causal link between income and center-based care among economically disadvantaged populations. I answer this call by applying an instrumental variables strategy to analysis of longitudinal data from the Fragile Families and Child Wellbeing Study (FFCWS) where I leverage state variation in access to state Earned Income Tax Credits as a quasi-experimental instrument for income. My results, which find a causal link between income and the use of center-based child care, suggest that economic support can foster enhanced early educational experiences that may have important implications for long-term patterns of attainment and achievement.

In chapter 3, I extend our limited knowledge of the long-term academic effects of center-based child care enrollment by filling a critical gap in integrated data that concurrently tracks family background, early childhood experiences, and reliable academic outcomes. To do this, I partnered with Dr. Sara McLanahan, the lead PI for the FFCWS at Princeton University, to propose a data-linking project to the Texas Education Research Center. Following a competitive approval process, I created an original dataset linking the Texas subsample of the FFCWS with Texas administrative school records to test the association between stable center-based child care enrollment and children's short- and long-term academic success across latent subgroups of sociodemographic risk. Results indicate population heterogeneity across indicators of school readiness, grade retention, and math and reading achievement scores. This work highlights the importance of creating integrated data systems to answer questions of both theoretical and practical importance. With a national movement towards expansion of public preschool education that is gaining momentum, understanding the long-term impact of early childhood programs is essential.

In chapter 4, the conclusion of my dissertation, I summarize the key findings from chapters 2-3 and outline next steps for this research project. This study is well-positioned to address important gaps in the literature by focusing on outcomes relevant to child care policy, while also exploring other policy-relevant avenues for increasing stable exposure to center-based child care among children from diverse low-income families. This is particularly important in light of the rise in non-parental child care coupled with persistent rates of child poverty in the U.S. Despite a well-documented association between income and academic success, studies have not considered the role of both income and income-support policies in shaping parental decisions around child care. By applying advanced statistical techniques to longitudinal data from the FFCWS, this work will contribute to our understanding of income, economic policies, patterns of child care exposure, and academic linkages.

Chapter 2.

Income and Stable Center-Based Child Care: Evidence from the Earned Income Tax Credit

ABSTRACT

Research clearly shows that early childhood poverty is a strong predictor of academic achievement and lasting adversity throughout life. Formal child care settings, such as center-based care, can serve to mitigate early life disadvantage, yet stable access to center-based child care is often out of reach for low-income families. A key policy question that remains unaddressed in the literature is whether modest increases in the incomes of working poor families would result in increased use of center-based child care. Further, identifying the effects of income on child care selection outcomes is inherently difficult, owing to the endogeneity of income. Applying an instrumental variables strategy to the analysis of longitudinal survey data (n = 2,548), I leverage state variation in access to the Earned Income Tax Credit (EITC) to predict the extent to which differences in family income affect stability and selection of child care arrangements. Results indicate that exogenous income increases (as a result of receiving state EITC transfers) are associated with significantly higher rates of center-based child care enrollment at age 3 and a higher likelihood of remaining in formal center-based arrangements between ages 1 and 3. Given a strong evidence base linking early child care type and stability with academic outcomes and human capital development, findings from this study suggest a policy-relevant mechanism by which increased income may decrease academic inequalities among children.

INTRODUCTION

Early childhood is a critical period for development. During these early years (defined as birth to age 5), flexibility and capacity for change in brain development and skill acquisition is at its greatest. Thus the consequences of early life economic disadvantage, including cognitive delays and lower academic achievement, can be particularly harmful, leading to persistent disadvantages across the life course (Currie & Almond, 2011; Johnson, Riis, & Noble, 2016; Noble et al., 2015) and increasing the socioeconomic stratification of society. Indeed, early childhood scholars believe that most of the socioeconomic gap in educational attainment forms before the age of 5, or even before the age of 3 (Duncan & Magnuson, 2013; Farkas & Beron, 2004; Heckman & Masterov, 2007; von Hippel et al., 2018). Early education programs have thus been highlighted for their potential to equalize opportunity and mitigate many of the detrimental effects of economic paucity that take root in early childhood (Magnuson et al., 2007; Weiland & Yoshikawa, 2013). In particular, stable exposure (i.e., without changes in providers or child care settings) to formal early care, such as a center-based or other educational preschool, has been shown to boost school readiness and to reduce the achievement gap between more and less disadvantaged children by improving short-term cognitive and academic outcomes (Magnuson & Duncan, 2016). Yet, compared to their higher-income counterparts, children raised in low-income households are far less likely to be exposed to stable center-based child care in early childhood (Capizzano & Adams, 2003; Meyers & Jordan, 2006). Household income, therefore, is not only of fundamental importance for academic success and attainment in general, but also potentially for the enrollment of children in enriching early child care programs. No studies to date, however, have examined the extent to which access to additional sources of income might contribute to increased enrollment in stable center-based care among children from diverse low-income families.

Understanding why some low-income parents invest in center-based child care while others do not, and the extent to which small changes in income might help explain part of this heterogeneity, is an important task for population and policy researchers. However, identifying the effects of income on parental decisions around child care is challenging to investigate empirically because of the endogeneity of income. To isolate the causal relationship between household income and child care enrollment patterns in this study, I used an instrumental variable (IV) approach along with adjustments for a comprehensive set of covariates to account for additional sources of selection bias in my estimations. For the identifying instrument in the IV estimation, I took advantage of the fact that a combination of factors, including disparate state Earned Income Tax Credit (EITC) policy and changes in policy between tax years, resulted in random differences in the amount of EITC transfers for which families were eligible. I limited my analysis sample to families for whom the EITC is most relevant—unmarried families with gross incomes below $45,000. Combining income information and longitudinal data with geographic indicators from the Fragile Families and Child Wellbeing Study (FFCWS), this study examines how differences in family income due to different levels of state EITC benefits affect patterns of child care use among low-income families.

My analysis advances this field of study in three ways. First, I make a novel contribution to our understanding of income, economic policies, and patterns of child care exposure by applying advanced statistical techniques and a quasi-experimental design to identify the effect of income on child care type and stability. To my knowledge, no previous studies have evaluated the degree to which small yet meaningful changes in income may impact low-income parents' selection of stable center-based child care. Second, I contribute to a more nuanced understanding of parental educational investments among low-income families by testing the extent to which family resources (e.g., income) serve as a general mechanism of selection into educational child care settings. Third, my findings, which suggest a causal link between income and the use of center-based child care, offer critical insights to inform the development of policies around early child care. Specifically, my results indicate that economic support programs targeting low-income families may foster enhanced early developmental experiences that can have important implications for long-term patterns of attainment and achievement.

BACKGROUND

Early Child Care Arrangements, Income, and Academic Achievement

Outside of the family, nonparental child care is one of the most important developmental contexts for young children (Cooper & Lanza, 2014; Crosnoe et al., 2014; Johnson, 2017; Laughlin, 2013; Sandstrom & Huerta, 2013). Given the significance of early childhood experiences in shaping long-term outcomes, exposure to cognitively stimulating and developmentally appropriate child care settings can serve as a protective factor for low-income children by attenuating the influence of risk factors that can compromise healthy development (Chaudry, Morrissey, Weiland, & Yoshikawa, 2017). Conversely, child care settings that do not offer sufficiently cognitively stimulating educational materials, activities, and interactions can have the opposite effect, to the detriment of child development (Bigras et al., 2010; Yoshikawa, Weiland, & Brooks-Gunn, 2016). Two important structural/organizational dimensions often used to characterize child care arrangements are *type* and *stability*.

A basic dichotomy used to describe nonparental child care *type* is formal center-based care by licensed providers (including public preschool and Head Start) versus informal home-based care by relatives or nonrelatives (Crosnoe et al., 2014). Compared to home-based settings, child care centers provide a more structured environment characterized by developmentally oriented curricula such as math and reading activities that are led by caregivers with higher levels of training and education (Dowsett et al., 2008). As a result, center-based care during infancy and early childhood has been associated with better cognitive and language development and better pre-academic skills relative to comparably evaluated home-based care (Brooks-Gunn, Han, & Waldfogel, 2002; Crosnoe et al., 2014; Dowsett et al., 2008; Duncan & Magnuson, 2013; National Institute of Child Health and Human Development [NICHD] & Duncan, 2003; NICHD ECCRN, 2000) or, especially for low-income families, care at home by a parent (Bernal & Keane, 2011; Loeb et al., 2007; Magnuson et al., 2007). These associations persist when child care quality is explicitly controlled for (Brooks-Gunn et al., 2002; NICHD & Duncan, 2003; NICHD ECCRN, 2000). These findings underscore the unique contribution of child care type to children's outcomes regardless of quality, which has been the focus of considerable empirical research beyond the scope of this paper.

Empirical evidence further suggests that duration and age of exposure to center-based child care may also influence child outcomes. Not many studies have examined the extent to which contiguous exposure to center-based care (e.g., two years versus one) yields larger effects, but of the few that have, findings suggest that, among disadvantaged children, those who experience an additional year of formal child care exhibit larger gains (Yoshikawa et al., 2016). Among students in the Chicago Longitudinal Study who enrolled in the Chicago Public Schools (CPS) in the mid-1980s, researchers found that children who were exposed to two years of the CPC center-based preschool program (relative to one) had higher test scores in kindergarten, and were less likely to receive special education or ever be held back by eighth grade (Arteaga, Humpage, Reynolds, & Temple, 2014). Turning to age of exposure, researchers using data from the NICHD Early Childcare Research Network (ECCRN) found cognitive benefits of enrollment in center-based care for children between the ages of 2 and 4.5, but not for children exposed before the age of 2 (NICHD & Duncan, 2003). Household income may not only affect the extent to which a family can access center-based child care but may also influence both age and duration of exposure to center-based care.

Stability of early child care arrangements is defined by the frequency of provider changes over time and the number of distinct care arrangements experienced in a given week (Johnson, 2017). Researchers generally agree that multiple child care transitions and the use of more than one source of care at a given time in early childhood each result in less consistent, stable, and predictable care environments, which can have negative impacts on development (Bratsch-Hines et al., 2017; Pilarz, Claessens, & Gelatt, 2016; Pilarz & Hill, 2014; Sandstrom & Huerta, 2013). Most findings on child care instability tend to be associated with poor social-emotional development and problem behaviors among low-income children (Johnson, 2017), although there are limited studies that also speak to negative cognitive outcomes. For instance, research finds that children who experience instability in early care arrangements tend to be less prepared for kindergarten than their counterparts who experience stable care (Ansari & Winsler, 2013; Loeb et al., 2004; Loeb et al., 2007; Tran & Winsler, 2011). Researchers posit that instability in early care settings may in fact counteract many of the academically beneficial aspects associated with center-based child care (Huston, 2017). Insofar as multiple provider changes over time and concurrent care arrangements may be associated with a lower dosage of educationally beneficial experiences, it is also plausible that instability in center-based child care may limit children from receiving “enough” beneficial inputs to offset the negative correlates of early life disadvantage (Johnson, 2017).

Exposure to Stable Center-Based Care

As outlined above, the benefit of stable center-based child care, especially for low-income children, is well established in the literature. At the same time, low-income families are at a disadvantage when it comes to enrolling their children in formal and stable child care arrangements (Coley et al., 2013). Using a representative sample of 6,250 children born in the U.S. in 2001, Crosnoe, and colleagues (2016) found that overall, low-income families (<185 percent Federal Poverty Level [FPL]) were significantly less likely to enroll a child in some form of center-based preschool at age 4 (63 percent) compared to their higher-income counterparts (76 percent). Similarly, examining early childhood program participation in the 2016 National Household Education Surveys Program, Corcoran and Steinley (2017) found that among parents with children ages birth to 5 enrolled in nonparental child care at least once per week (exclusive of kindergarten), 53 percent of low-income families with household incomes in the range of $20,001-$50,000 enrolled their children in center-based care, compared to 69 percent of families earning upwards of $100,000. Indeed, low-income parents report that the price of highly regulated, and possibly higher quality, arrangements such as center-based child care often serves as a barrier to entry. Crosnoe et al. (2016) found that in 2001, parents who reported needing reasonably priced child care options were less likely to choose center-based care (exclusive of Head Start). In comparative terms, Corcoran and Steinley (2017) reported that 64 percent of families with household incomes of $20,001-$50,000 rated cost as “very important” in terms of factors used to select weekly care arrangements, compared to 49 percent of households in the $75,001-$100,000 range and 37 percent reporting $100,000 or more. Similarly, cost was a “very important” selection factor for 61 percent of single-parent households versus 48 percent of two-parent households.

Low-income families also find it more difficult than their more affluent counterparts to access and maintain consistent child care arrangements in a single-provider setting (Chaudry, 2004; Laughlin, 2013; London et al., 2004). For example, using U.S. census data, Laughlin (2013) found that in 2011, nearly 26 percent of children aged 5 and younger who lived with working mothers in households below the federal poverty threshold experienced multiple child care arrangements, compared to 20 percent of all children. Research on child care stability among low-income households who receive government subsidies to pay for child care also indicate high levels of instability over time (Henly et al., 2015; Meyers et al., 2002).

Insofar as parents' child care arrangements are constrained by price and family income, the expectation would be that attenuating the influence of one or the other would lead to increased consumption of center-based care. Although evidence suggests that formal child care arrangements tend to increase with family income (Meyers & Jordan, 2006) and the risk of concurrent child care (i.e., multiplicity) decreases significantly among higher-income families (Sandstrom & Huerta, 2013), the issue of how and why low-income families select into various types of child care is complicated and not well understood either theoretically or empirically. In this study, I examined the extent to which a small yet meaningful increase in income changes low-income parents' child care enrollment patterns to elucidate how economic resources might help encourage enrollment in stable center-based care.

Theoretical Perspectives on Child Care Selection

Rooted in economic theory, the parental investment perspective suggests that, given access to relevant resources, parents will choose to invest in materials, services, and a home environment that maximizes their children's human capital development (Becker, 1981; Becker & Tomes, 1986). Thus, parental investment theory suggests that, out of concern for their children's future well-being, low-income parents will be more likely to invest in early educational opportunities such as center-based child care when they have the resources to do so.

A major assumption made in this formulation, however, is that selection into specific child care types and stability operates only through economic resources. Given observed heterogeneity in child care enrollment across a range of socioeconomic and sociodemographic groupings, this seems unlikely. Indeed, literature on parental investment in children suggests that spending as parental investment[2] is influenced by a combination of household income, family structure, and characteristics of both the children and parents in the household (Kornrich & Furstenberg, 2013). A wealth of empirical studies find evidence for this, confirming that enrollment varies across a wide range of family selection factors including household poverty level as a percentage of FPL and receipt of welfare, race/ethnicity, family structure, number of children and other kin in the household, child age and gender, and maternal age, educational attainment, depression, and work schedule (see Kimmel, 2006 and Meyers & Jordan, 2006 for a more in-depth review). Recognizing the importance of addressing a variety of family selection factors, I argue that, given the often prohibitive cost of center-based child care for low-income families and the consequential nature of stable center-based care for children from low-income families, it is also important that we look at the effect of family resources in isolation. In this study, therefore, I test a model of parental investment that includes a comprehensive set of socioeconomic and sociodemographic factors to adjust for family selection into child care type and stability. Although an important element of the analysis, however, these additional controls are not sufficient to ensure that all sources affecting selection into specific child care arrangements are captured.

[2] Although time is another important form of parental investment, parental spending on children is typically assumed to be at the root of long-term patterns of superior attainment and achievement of children from wealthier families (Kornrich & Furstenberg, 2013).

Measuring the Causal Role of Income on Stable Center-Based Care

To isolate the causal role of income on child care arrangements among low-income families, the endogeneity of income must be addressed. Statistical endogeneity, in this case, results from unobserved determinants of household income that also influence child care selection, unobserved measurement error in income, or both. Children growing up in low-income families often face adverse circumstances and challenges that may constrain or shape exposure to child care arrangements regardless of changes in family income. In addition, factors such as state-level policies and changes in family circumstances like parental job loss, moving to a new neighborhood, or illness of parent or child may affect both family income as well as patterns of child care selection. As a result, empirical studies that do not separately identify effects caused by changes in income from effects of changes in other unmeasured family circumstances can produce biased results. Borrowing from an emerging literature that uses advanced methodological approaches to distill the causal effects of income on short- and long-term academic outcomes (e.g., Dahl & Lochner, 2012), this study takes advantage of an instrumental variables (IV) design to reduce selection bias in the observational data. I use expected state-based EITC transfers as an instrument to identify exogenous variation in household income, and estimate the unbiased local average treatment effect of income on exposure to child care type and stability.

The EITC is a refundable tax credit that supplements the earnings of low-wage parents. Because the credit is refundable, taxpayers may benefit from the EITC even when they have no tax liability (Nichols & Rothstein, 2015). The basic structure of the federal EITC is a trapezoid, where benefits increase along with income, reaching a plateau and then decrease as earnings continue to rise. Given the gradual phase-in/phase-out structure, the EITC aims to incentivize work. Of all EITC-eligible low-wage workers, approximately 86 percent actually receive the credit (Shanks & Danziger, 2010). The majority of EITC recipients (61 percent in 2008) are in households headed by an adult without a college education. Single mothers represent nearly one-third of EITC recipients and receive more than 40 percent of all EITC funds (Athreya, Reilly, & Simpson, 2012). Only 5 percent of EITC dollars go to adults without children (Meyer, 2010).

In addition to the federal EITC, state EITCs were introduced in the late 1980s and gained momentum in the late 1990s and early 2000s, following welfare reform (Bastian & Michelmore, 2017; Hoynes, Rothstein, & Ruffini, 2017). States vary in terms of when they implemented EITCs, their overall generosity, whether the credits are refundable, and whether they have changed their generosity over time. As of 2017, 29 states and the District of Columbia had implemented state EITCs (Center on Budget and Policy Priorities, 2017). A function of the tax year, state of residence, marital status, number of dependent children, and income of a given household, state EITCs are typically set as a share of the federal credit and range from 3.5 percent to 45 percent of the federal benefit (Hoynes et al., 2017). Table 2.1 shows state EITCs between 1997 and 2015 for the 15 states included in the FFCWS analytic sample for this study. Seven states had EITCs at some point during the 1998 to 2003 period—the observation period of this study—with benefits ranging from 5 percent to 30 percent of the federal benefit (or 4 percent and 43 percent for households with one and three children in Wisconsin, respectively).

Natural policy variation between and within states over time (i.e., between-state EITC creation and within-state EITC expansion) allows for a quasi-experimental evaluation of the effect of exogenous variation in family income on child care type and stability. That is, differences in income resulting from EITC policy benefits are random, because individuals with the same characteristics will receive different payment amounts depending on the tax year and their state of residence (Jones & Michelmore, 2016).

Table 2.1. State EITC benefits as a proportion of federal EITC in 15 FFCWS states.

Child Age at time of survey:		0	0; 1	0; 1	1; 3	3	3; 5	5	5		9	9	9				15	15	15
Year:	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
California	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	0.425
Texas	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
Maryland	--	0.10	0.10	0.15	0.16	0.16	0.18	0.20	0.20	0.20	0.20	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Michigan	--	--	--	--	--	--	--	--	--	--	--	0.10	0.20	0.20	0.20	0.06	0.06	0.06	0.06
New Jersey	--	--	--	0.10	0.15	0.175	0.20	0.20	0.20	0.20	0.20	0.225	0.25	0.20	0.20	0.20	0.20	0.20	0.20
Pennsylvania	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
Virginia	--	--	--	--	--	--	--	--	--	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Indiana	--	--	--	--	--	--	0.06	0.06	0.06	0.06	0.06	0.06	0.09	0.09	0.09	0.09	0.06	0.09	0.09
New York	0.20	0.20	0.20	0.225	0.25	0.275	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30
Massachusetts	0.10	0.10	0.10	0.10	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
Tennessee	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
Illinois	--	--	--	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.10	0.10
Florida	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
Ohio	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	0.05	0.05
Wisconsin (1 child)	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Wisconsin (2 child)	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.11	0.11	0.11	0.11	0.11
Wisconsin (3 child)	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.34	0.34	0.34	0.34	0.34

Source: Adapted from Jones and Michelmore (2016).

Present Study

To address the aim of this study, I use restricted FFCWS data with geographic indicators to empirically assess the extent to which differences in family income resulting from a state EITC benefit affect patterns of child care type and stability among low-income families eligible for EITC transfers. Drawing on the family investment perspective, I expect additional exogenous income to affect child care arrangements because it increases economic resources that mothers have at their disposal to invest in their children, and provides a lump sum payment that can be used for more enriching early child care arrangements. Increases in income based on state EITC transfers should not reduce work (and therefore time spent in parent care), because EITC eligibility is contingent on paid work. The following three hypotheses summarize the expected relationship between a policy-induced increase in income and child care type and stability:

> *Hypothesis 1:* an exogenous increase in income is likely to increase the use of formal center-based child care at ages 1 and 3.
>
> *Hypothesis 2:* an exogenous increase in income should increase the likelihood of entering and remaining in formal arrangements between ages 1 and 3.
>
> *Hypothesis 3:* an exogenous increase in income may reduce the likelihood of child care instability as measured through child care multiplicity and backup arrangements at age 1 and 3, and total provider changes between birth and age 3.

Insofar as exposure to educational child care can minimize socioeconomic stratification in the U.S., this research expands both empirical and theoretical knowledge about differential child care exposure as a mechanism of socioeconomic stratification in the U.S.

RESEARCH DESIGN AND METHODOLOGY

Data

The Fragile Families and Child Wellbeing Study (FFCWS) is a longitudinal multi-method cohort study of 4,898 families in 20 U.S. cities representing 15 states. Families were initially surveyed at the birth of the focal child of the study, between 1998 and 2000, and followed through age 15 over six waves of data collection (focal child ages 0, 1, 3, 5, 9, and 15, respectively). The FFCWS data were collected from a stratified random sample of U.S. cities with populations of 200,000 or more and are representative of all nonmarital births in large U.S. cities when weights provided within the study are applied (for additional details on sampling, see Reichman, Teitler, & McLanahan, 2001). The FFCWS study design oversamples nonmarital births, wherein nearly three of every four mothers recruited to the study were unmarried. Mothers were thus more likely to be single or living with a non-biological (i.e., social) father and therefore experience higher prevalence rates of partner transitions, financial instability, and low-income status than the general population.

The restricted FFCWS data—which include geographic state indicators for each family—are well suited for estimating the effect of household income on child care type and stability. Detailed questions about child care arrangements were asked at the one- and three-year post-birth interviews, including questions about child care type, number of child care transitions, and concurrent and backup care arrangements. The FFCWS also asked questions about household income, marital status, and number of dependent children, which, together with geographic indicators, were used to construct estimates of federal and state EITC benefit eligibility. The distribution of families across states and over time created natural variation in EITC benefit amounts. Eligible state EITC credit amount (the instrumental variable for this study) was measured at the one- and three-year post-birth interviews. Of the 15 states included in the

FFCWS (see Table 2.1), 4-6 states had a state EITC at the age 1 interview (between 1999 and 2001), and 6-7 had a state EITC at the age 3 interview (between 2001 and 2003).

The analytic sample for this study uses observations from the first three waves of data collection (focal child ages 0, 1, and 3). Families were excluded from the sample for this study if they were not interviewed at the second and third wave of the study (child ages 1 and 3; n = 312), had a focal child who lived with them for less than half of the time in either wave (n = 96), or did not have data on state of residence at baseline (n = 4). In addition, the sample was limited to families that were potentially eligible for the federal EITC, and therefore excludes families with adjusted gross income (AGI) above $45,000 at the age 1 or 3 survey (n = 603). Finally, given extensive research that finds the largest EITC program impact to be for single-mother families and for families with two or more children (Dahl & Lochner, 2012), the sample was further limited to unmarried mothers at the time of the age 1 survey (n = 1,335 observations excluded), yielding a final analytic sample of 2,548 mother-child dyads. To explore the extent to which child care type and stability vary by the presence of one versus two or more children in the household, analyses were stratified by the number of dependent children in the household at the age 1 interview. Item-missingness on predictor variables did not exceed 9 percent, and was addressed through multiple imputation of 20 data sets based on the MI suite in Stata 15. Following von Hippel (2007), I included the outcome variables in the imputation equation but dropped children with imputed y-values from the analysis. Complete case analysis revealed a similar pattern of results, indicating that patterns of item-missingness do not alter substantive conclusions (results available upon request). National sampling weights were not applied, as these are less appropriate in causal analysis (Solon, Haider, & Wooldridge, 2015) and when using a sub-sample of survey respondents. My analyses do, however, control for the key characteristics for which the weights adjust: maternal marital status at birth, age, race/ethnicity, and education.

Measures

Child Care Type and Stability

Measures of child care type and child care stability are the dependent variables for this study. Measured at the age 1 and 3 interviews, the series of indicator variables used to assess primary *child care type* were collapsed into three primary care types: (1) parent, (2) informal family child care (e.g., home-based child care settings, including being cared for by a relative or nonrelative in the family's home), and (3) formal center-based care (inclusive of center-based care, Head Start, Early Head Start, and public pre-K). Children who were reportedly in care for less than 10 hours per week were coded as parent care. *Child care stability* was assessed through a series of four mutually exclusive child care sequences between child ages 1 and 3: (1) informal only care in both years (informal care includes both parent and family child care), (2) entry formal, meaning informal care at age 1 and formal care at age 3, (3) exit formal, meaning formal care at age 1 and informal care at age 3, and (4) stable formal, meaning formal care in both years.

Child care stability was further assessed through measures of child care multiplicity, use of backup arrangements, and total number of child care transitions between birth and age 3. Capturing child care multiplicity, two binary variables indicated whether a mother was currently using two or more child care arrangements at the time of the age 1 and 3 interviews (1 if yes, 0 if otherwise). Likewise assessed through two binary variables, use of backup arrangements was based on mother report of one or more special child care arrangements in the past month at the time of the child age 1 and 3 interviews (1 if yes, 0 if otherwise). Finally, an additional indicator of long-term child care instability was constructed to capture the total number of child care provider transitions reported between birth and age 3.

Net Income

To measure household income, the FFCWS asked mothers at each wave of data collection to provide an exact dollar amount (or if unknown, a range) of household income. First imputing household income amounts for participants who reported a range, the FFCWS team then imputed dollar amounts for the approximately 10 percent of participants with missing income data. From this constructed measure of total household income, I then subtracted all unearned income (i.e., TANF, Food Stamps, and child support amounts reported in the FFCWS) to derive pretax/pre-benefit household income data that, along with other income sources and amounts, was used to calculate federal and state income tax liabilities or refunds through the National Bureau of Economic Research's TAXSIM version 27.[3] The combined state and federal tax liability (or refund) was then deducted from (or added to) the total household pretax income to capture posttax/post-benefit net income. Income is inflation-adjusted and presented in year 2000 U.S. dollars.

EITC Benefit

In addition to sources of income described above, TAXSIM incorporates information on state of residence, tax year, filing status, and number of dependents to calculate a combined state and federal EITC dollar amount for which a given family is eligible. This EITC benefit amount, or exogenous source of variation in income, serves as the instrument used to estimate the relationship between income and child care type and stability.

[3] National Bureau of Economic Research (2017). TAXSIM, version 27. http://www.nber.org/taxsim/.

It is important to note that this instrument assumes full take-up of state and federal EITC, as TAXSIM does not allow for a determination of actual recipients. Previous participation estimates are approximately 80-87 percent among eligible families (Maynard & Dollins, 2002; Shanks & Danziger, 2010), however, prior studies have used this strategy with the expectation that results would be biased toward null or underestimations of the true effect (e.g., Berger, Font, Slack, & Waldfogel, 2017; Dahl & Lochner, 2012).

Prior research finds that EITC recipients exhibit a tendency to "bunch" around the level of earned income at which the credit amount is maximized (Chetty, Friedman, & Saez, 2013), indicating the potential for selection, where parents target their work income to maximize EITC benefits. However, because specific income requirements for EITC benefits change from year to year, selection bias is reduced (Dahl & Lochner, 2012). To check for remaining selection bias, I calculated a second imputed EITC benefit based on a two-year lag of mothers' demographic and income data. This new calculation based on lagged household income remains highly correlated with current income. Results are available upon request.

Time-Varying Covariates

Poverty level was a set of constructed poverty categories measuring household income as a percentage of the Federal Poverty Level (FPL) and collected at each wave of the FFCWS (0-49 percent, 50-99 percent, 100-199 percent [reference category], 200-299 percent, or 300 percent+). Family structure was categorized as two-parent cohabiting or single-parent household (reference category). Additional covariates included: mother's age, mother's educational attainment (less than high school [reference category], high school or equivalent, some college, or college degree or more), number of children in the household (1 if one child; 2 if two or more), focal child age, maternal depression (1 if meets depression criteria; 0 if otherwise), the presence of a grandparent in the household (1 if present, 0 if otherwise), and maternal employment status (full-time [reference category], part-time, unemployed, or enrolled in school or a job training program). Census tract unemployment levels and tax filing year fixed effects were included to control for state-year level factors, as well as state dummy variables to control for unobserved local conditions that may co-occur with changes over time in EITC benefits.

Time-Constant Covariates

Measured at baseline, time-constant covariates included: race and ethnicity (white [reference category], black, Latinx, or other); and child gender (1 if female, 0 if male). Because work support benefits are largely based on a continuous measure of total earnings and total number of dependent children per family, measures of these variables at the time of the age 1 survey were also included as controls.[4] Finally, dummy-coded measures of participation in other safety net programs (namely, TANF, Food Stamps, and SSI) were also included.

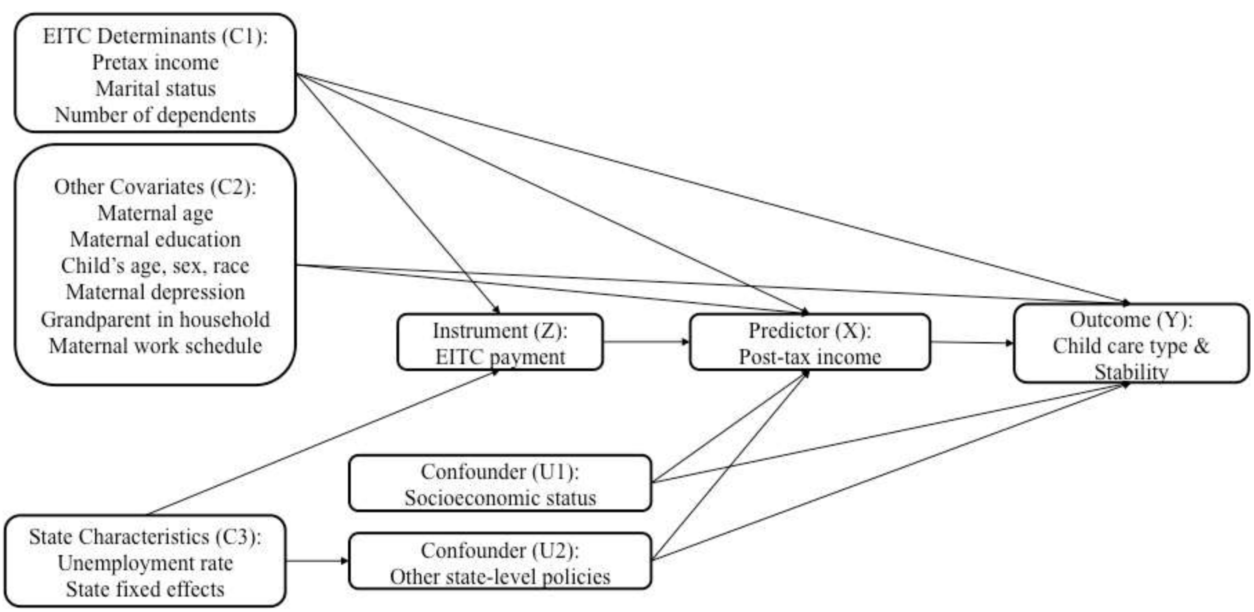
Analysis Strategy

The main goal of this analysis was to investigate the causal effect of income on measures of child care type and stability. However, because pretax household income is likely correlated with a number of unobserved factors such as socioeconomic status or other unmeasured state-level policies that may affect both posttax income and parental child care choices, income is endogenous and applying standard regressions can produce biased results. Endogeneity was addressed in this study by using a comprehensive set of covariates and applying a two-stage-least-squares (2SLS) IV approach. Through this technique, I was able to isolate non-endogenous variation in family income and obtain consistent estimates of the impact of income on child care type and stability.

[4] Note, total number of dependent children were not included in split models.

Illustrated in Figure 2.1, IV analysis is appropriate in this case because it accounts for the fact that the relationship between income (X) and child care enrollment patterns (Y) is confounded by unobserved characteristics (U) that may also affect child care type and stability (Y). To overcome this challenge, IV analysis relies on the existence of a quasi-randomly assigned variable (Z) that impacts child care choices (Y) only through posttax income (X). Following a growing literature that uses EITC benefits as an instrument for income (e.g., Berger et al., 2017; Dahl & Lochner, 2012), I assumed that, because variation in the size of EITC payments over time is driven by exogenous policy changes, EITC benefit amount affects the decision to enroll one's child in stable center-based care only through its impact on posttax income.

Figure 2.1: Instrumental Variables Design.



To account for residual confounding that may persist if the EITC benefit is correlated with the error term (e.g., states with more generous EITCs may differ from states with smaller or no EITCs on characteristics associated with child care enrollment), I control for state characteristics (C1) including census tract unemployment rate and state and year fixed effects.

To account for the fact that variation in EITC amount is partly a function of household characteristics that determine EITC eligibility and payment size, I account for pretax income, marital status,[5] and number of dependents (C2). Specifically, to address variation in EITC payments that result from changes in marital status and number of dependents, I hold each of these factors constant at their baseline (wave 1) value. To account for endogenous changes in family income, in addition to a measure of lagged pretax income, I include a lagged indicator of zero pretax income to flexibly model income (Berger et al., 2017; Dahl & Lochner, 2012; Hamad & Rehkopf, 2016). Finally, to account for time-invariant mother- and child-level characteristics (C3), the covariates described above are also included in these models.

Although some researchers have suggested two-stage residual inclusion (2SRI) estimators to estimate local average treatment effect (LATE) parameters in models with binary or nonlinear outcomes in the second stage equation (e.g., Terza, Basu, & Rathouz, 2008), recent literature (e.g., Basu, Coe, & Chapman, 2018) finds that 2SRI methods are more likely to produce biased estimates of both average treatment effects (ATE) and LATEs, and many analysts favor the 2SLS approach in cases where second stage outcome variables are nonlinear (e.g., Chapman & Brooks, 2016). Thus the LATEs estimated in the 2SLS IV models in this study capture the average causal effect of income on the probability of parental selection patterns regarding the nonlinear outcomes of child care type and stability among families whose income differs based on the level of EITC benefits. These estimates reflect the LATE rather than ATE because the effect of income is only “locally” interpretable in the context of EITC benefits (Basu et al., 2018).

[5] Note, mothers who are married at the birth of the focal child are excluded from the analytic sample. As a result, IV estimations control for the extent to which a mother is single or cohabiting.

The two-staged empirical specification to estimate the relationship between income and child care type and stability in this study is as follows:

$$Income_i = \beta_0 + \beta_1 EITC_i + \beta_2 X_i + \beta_3 \alpha_{st} + \beta_4 Zero_{i,W-1} + \beta_5 PreInc_{i,W-1} + \delta_s + \gamma_t + \varepsilon_1 \quad (1)$$

for the first stage and

$$Y_i = \beta_0 + \beta_1 \widehat{Income}_i + \beta_2 X_i + \beta_3 \alpha_{st} + \beta_4 Zero_{i,W-1} + \beta_5 PreInc_{i,W-1} + \delta_s + \gamma_t + \varepsilon_i \quad (2)$$

for the second stage. Y_i denotes, alternatively, child care type, child care sequences, and three measures of child care stability; $Income_i$ is the endogenous variable indicating posttax/post-benefit household income; $EITC_i$ is the combined federal and state EITC benefit amount; and $\widehat{Income}_i$ is the first-stage predicted value of $Income_i$. In both model sets, X_i is a row vector of demographic controls as outlined in the measures section, α_{st} accounts for state-year level contextual controls (i.e., census tract unemployment), state fixed effects are represented by $\delta_{s,}$ and γ_t denotes tax year fixed effects.

In a 2SLS IV approach, the IV estimator uses only a portion of the variance in the instrumented variable, typically producing large second stage standard errors. Thus, to test the robustness of my findings, I also ran each model (with a few noted exceptions due to insufficient cell sizes for model convergence) with bootstrapped standard errors estimated in the first and second stage together as a sensitivity analysis (Newey, 1987). Coefficients in the multinomial logistic regression models are presented as relative risk ratios (RRR). Much like odds ratios (OR), less than one indicates reduced likelihood and greater than one indicates increased likelihood of being in a given group versus the comparison group.

RESULTS

Descriptive Statistics

Table 2.2 presents a descriptive picture of household income and EITC eligible benefit amount, child care type and stability, and other household, mother, child, and state characteristics from the FFCWS study sample. The first column shows results for the full sample, followed by results for families living in states with and without state EITC benefits at child age 1. The final column indicates statistical difference in variable proportions and means between EITC and non-EITC states. Most children were in parent care at age 1 (57 percent). Another 28 percent were in family child care, and nearly 15 percent were in center-based care. This shifted towards center-based care by age 3 such that 43 percent of children were in parent care, 28 percent were in family child care, and the remaining 30 percent were in center-based care. At age 3, children living in states with an EITC were less likely to be in family child care (23 percent versus 29 percent) and more likely to be in center-based child care (34 percent) than children living in states without an EITC (28 percent). Between ages 1 and 3, about 65 percent of all children in the sample had been exposed only to informal child care arrangements (either parent or family child care), and just under 10 percent experienced stable center-based care in both years of measurement. Although only marginally significant, children in EITC states were less likely to experience only informal care at both ages 1 and 3 ($p<.1$). In terms of entry into formal care (formal child care at age 3, but not 1), children in states with their own EITC were more likely to enter formal care at age 3 (24 percent), compared to only 19 percent of their non-state EITC counterparts. Most children experienced no child care transitions between birth and age 3 (56 percent), followed by 1 transition (18 percent), 2 transitions (14 percent) and 3 or more transitions (12 percent), which were less likely in EITC states. Child care multiplicity was not common at age 1 (6 percent) or 3 (7 percent), although approximately 12 percent of households had backup arrangements at age 1 and nearly 17 percent at age 3.

The average mother in this sample had a net income of $13,900 at the time of the age 1 survey, and upwards of $15,400 at the time of the age 3 survey. The average total EITC transfer (federal and state combined) was about $1,400 at the time of the age 1 survey (between 1999 and 2001), and nearly $1,600 during the age 3 survey (between 2001 and 2003). At the age 1 survey, nearly two-fifths of mothers lived between 0 percent and 49 percent of the poverty line, another quarter lived between 50 percent and 99 percent of the poverty line, and nearly one-third ranked between 100 percent and 199 percent of the line. Families in non-EITC states were more likely to live between 100 percent and 199 percent of the federal poverty line than those in EITC states. During the study interval, nearly 5 percent of families received SSI (shifting to 4 percent versus 6 percent when looking at non-EITC and EITC states, respectively), about two-fifths of families received TANF, and over half (55 percent) depended on food stamps. Most households had at least two dependent children (65 percent), and nearly one-fourth lived with a grandparent in the home.

Among the sample of unmarried mothers observed in this study, most were single, with just under 40 percent in a cohabitating relationship. Most mothers in the sample had less than a high school degree (41 percent), followed by approximately one-third of mothers with a high school degree (or equivalent), and just under 25 percent reporting some college. Under 30 percent of mothers worked full time; nearly 10 percent worked part-time, over 40 percent were unemployed, and another 20 percent reported being in school. The average maternal age at the birth of the focal child was about 25, and approximately 17 percent of mothers reported signs of depression at the age 1 interview. Across the entire sample, about 12 percent of mothers selfidentified as White, 69 percent as Black, and 27 percent as Hispanix. Mothers in EITC states were less likely to identify as White or Hispanix, and more likely report their race as Black. At child age 1 (one year after the baseline survey), ten of the fifteen states, representing 72 percent of the study sample, had no implemented state EITC. Non-EITC states were more likely to have lower unemployment rates. Taxes were assessed in the year 2000 for most families: 50.43 percent of mothers in the full sample shifting to 74 percent in EITC states and only 42 percent in non-EITC states.

Table 2.2. Descriptive statistics for sample, by state EITC (percentages and means).

	Total Sample	No State EITC	State EITC	
Child Care Type and Stability Measures				
Child Care Type at age 1				
Parent (P)	57.28	56.24	60.06	+
Family Child Care (FCC)	28.28	28.61	27.40	
Center-Based Care (CBC)	14.44	15.15	12.54	+
Child Care Type at age 3				
Parent (P)	42.70	42.85	42.30	
Family Child Care (FCC)	27.53	29.08	23.43	**
Center-Based Care (CBC)	29.77	28.07	34.28	**
Child Care Exposure from age 1 to 3				
Informal Only	64.93	66.07	61.90	+
Entry Formal	20.66	19.09	24.83	**
Exit Formal	4.85	5.27	3.74	
Stable Formal	9.56	9.58	9.52	
Child Care Transitions from birth to age 3				
No transitions	56.27	55.05	59.39	
1 transition	17.9	17.81	18.12	
2 transitions	13.96	14.04	13.76	
3 or more transitions	11.87	13.10	8.73	**
Multiplicity at age 1	5.92	5.99	5.73	
Multiplicity at age 3	7.19	7.12	7.37	
Use of Backup Arrangements at age 1	11.77	11.77	11.76	
Use of Backup Arrangements at age 3	16.75	16.49	17.45	
Income and Potential EITC benefit				
Net Income at age 1 (mean)	13887.18	14004.03	13574.48	
Net Income at age 3 (mean)	15481.16	15866.69	14457.94	*
Potential EITC benefit at age 1 (mean; instrument)	1418.18	1323.88	1670.548	***
Potential EITC benefit at age 3 (mean; instrument)	1577.70	1514.13	1746.61	**
Pre-tax income (mean)	13385.59	13665.03	12640.89	*
Zero household income	1.1	1.02	1.30	
Household, Mother, and Child Characteristics				
Household Characteristics				
Poverty Level as a percentage of FPL				
0-49% FPL	38.04	37.46	39.57	
50-99% FPL	25.53	25.25	26.28	
100-199% FPL	28.77	29.88	25.81	*
200-299% FPL	6.82	6.54	7.57	
300+% FPL	0.84	0.87	0.77	
Receipt of SSI	4.49	3.90	6.07	*
Receipt of TANF	37.43	37.68	36.74	
Receipt of Food Stamps	54.58	53.78	56.70	
Dependent children in household				
1	34.58	33.98	36.17	

Table 2.2, continued. Descriptive statistics for sample, by state EITC (percentages and means).

	Total Sample	No State EITC	State EITC	
2+	65.42	66.02	63.83	
# dependent children in home (mean)	2.28	2.27	2.31	
Grandparent in home	22.46	21.71	24.45	
Family Structure				
Mother is Cohabitating	37.72	37.87	37.31	
Mother is Single	62.28	62.13	62.69	
Maternal Characteristics				
Maternal Education				
Mother has less than HS	40.75	40.41	41.64	
Mother has HS or GED	33.28	34.25	30.69	+
Mother has some college	24.09	23.77	24.93	
Mother has college or graduate degree	1.89	1.57	2.74	+
Maternal Employment Status				
Mother works full-time	27.89	28.97	25.00	*
Mother works part-time	9.28	9.41	8.96	
Mother is unemployed	43.23	42.86	44.22	
Mother is in school	19.59	18.76	21.82	+
Race/Ethnicity				
White	11.84	13.57	7.22	***
Black	58.62	54.35	69.99	***
Hispanix	27.18	29.53	20.92	***
Other	2.36	2.54	1.88	
Maternal age at birth of focal child (mean)	24.93	24.77	25.35	*
Maternal Depression	17.19	16.57	18.86	
Child Characteristics				
Child age (in months) (mean)	15.20	15.45	14.54	***
Child is female	47.72	48.00	46.97	
State Characteristics				
Unemployment Rate at age 1 (mean)	3.95	3.83	4.25	***
Tax Year (one year lag of age 1 interview)				
1998	13.74	18.88	0.00	***
1999	35.83	39.48	26.08	***
2000	50.43	41.64	73.92	***
State				
California	12.09	16.61	0	
Texas	15.31	21.04	0	
Maryland	7.1	0	26.08	
Michigan	7.46	10.25	0	
New Jersey	7.1	9.76	0	
Pennsylvania	8.95	12.30	0	
Virginia	8.99	12.35	0	
Indiana	6.79	9.33	0	
Wisconsin	8.24	0	30.26	

Table 2.2, continued. Descriptive statistics for sample, by state EITC (percentages and means).

	Total Sample	No State EITC	State EITC
New York	6.83	0	25.07
Massachusetts	2.0	0	7.35
Tennessee	2.0	2.75	0
Illinois	3.06	0	11.24
Florida	2.0	2.75	0
Ohio	2.08	2.86	0
N	2,548	1,854	694

Notes: Chi-square tests indicated significant differences in variables between families living in states with and without an EITC at the time of the age 1 interview. *t*-tests were used for testing significance in mean scores.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Income and Type of Child Care

The next stage of analysis explored the relationship between income and child care type. Figures 2.2 and 2.3 depict the predicted probably of each type of child care at ages 1 and 3, respectively. Consistent with hypothesized results, we see that as household income increases from $0 to $45,000, so too does the probability of the child being in center-based child care at either age. At age 1 (see Fig. 2.2), mothers with zero and low levels of income were most likely to rely on parent care. As income increased, the likelihood of parent care precipitously declined, with frequency of use falling below family care at around $30,000 of net household income, and center-based care at just under $40,000. The positive relationship between use of center-based care and income was more pronounced at age 3. In Figure 2.3 we see a steep increase in the use of center-based care as income rises, surpassing both parent and family child care at around $15,000 of net household income.

Figure 2.2: Predicted Probabilities for Child Care Type at Age 1 by Household Income.

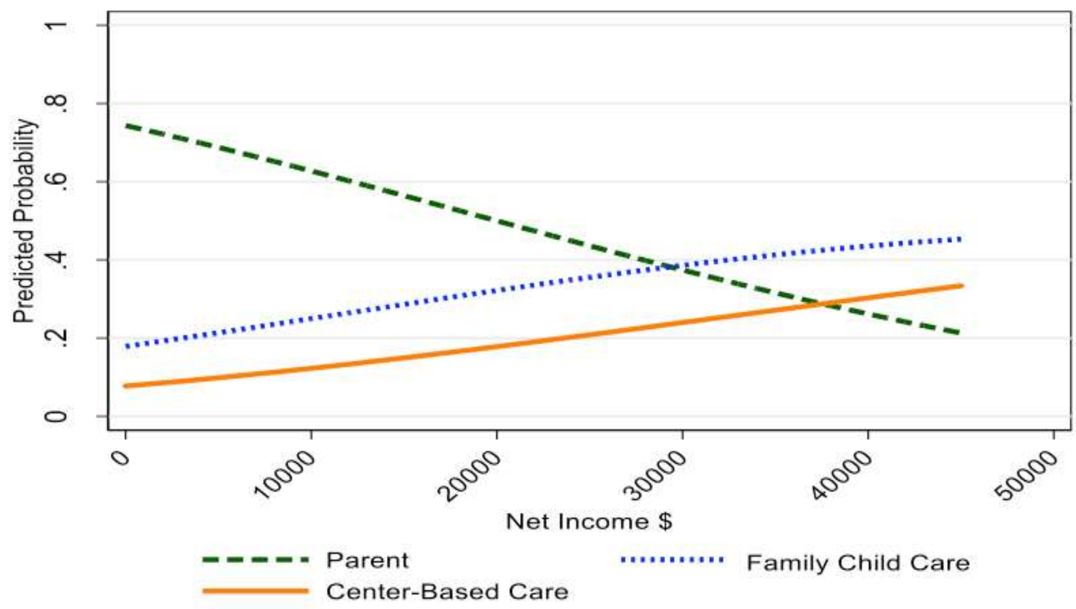


Figure 2.3: Predicted Probabilities for Child Care Type at Age 3 by Household Income.

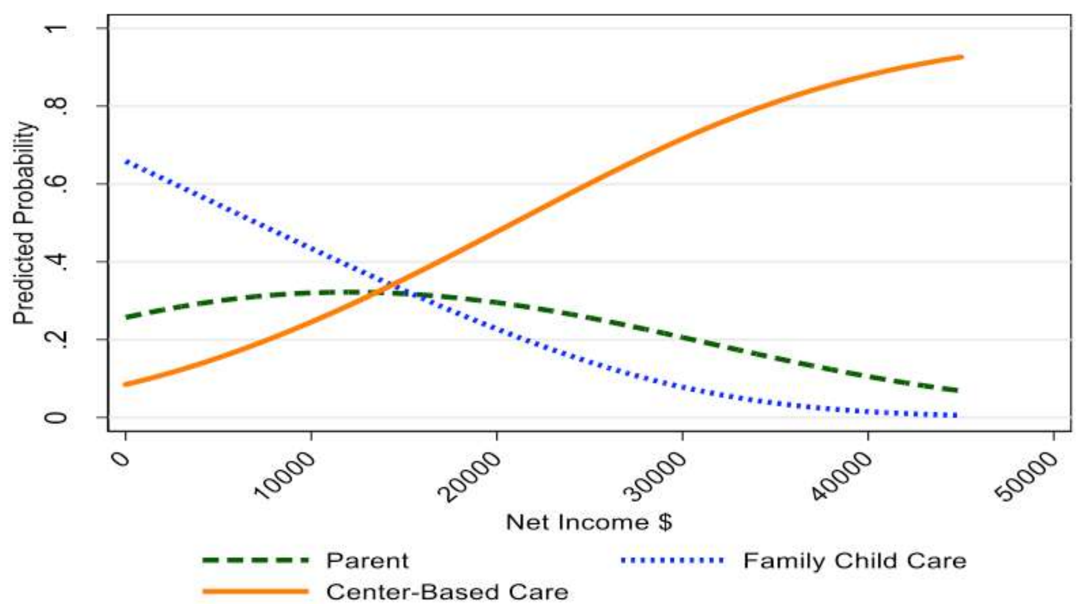


Table 2.3 documents results from the 2SLS IV multinomial logistic models, showing the relationship between an exogenous increase in household income and child care type, after accounting for covariates and controlling for stable effects of state, state unemployment rates, and tax year. For 1-year-old children, there was a nonsignificant trend toward higher rates of center-based child care with increased income. For 3-year-olds, however, mothers who received (or were eligible to receive) $1,000 in EITC benefits two years prior were 26 percent more likely to use center-based child care over parent care, and 29 percent more likely to enroll their child in center-based care over informal family child care arrangements. This relationship held for mothers with two or more dependents. For mothers with only one dependent child in the household, although results reveal larger odds of center-based care over parent care, and substantially larger odds of enrolling their child in center-based care versus family child care, these trends were not statistically significant at the $p<.05$ level. To explore the extent to which income from state EITC benefits received in the same year impacted age 3 child care enrollment, I reran the age 3 model using wave three (corresponding to child age 3) EITC benefits to instrument for net household income in the same wave. Under this new formulation, a $1,000 increase in income significantly increased the likelihood of center-based care enrollment over parent care by 12 percent for all mothers, 11 percent for those with two or more dependents, and 30 percent for mothers with only one dependent child.

Table 2.3. Effect of income on child care type.

	Full Sample RRR (SE)						One Dependent RRR (SE)						Two+ Dependents RRR (SE)					
	Parent vs.:		FCC vs.:		CBC vs.:		Parent vs.:		FCC vs.:		CBC vs.:		Parent vs.:		FCC vs.:		CBC vs.:	
	FCC	CBC	Parent	CBC	Parent	FCC	FCC	CBC	Parent	CBC	Parent	FCC	FCC	CBC	Parent	CBC	Parent	FCC
Age 1 Child Care Type																		
Income	1.04	1.13	0.96	1.09	0.89	0.92	1.35	87.27	0.74	64.65	0.01	0.02	0.97	1.05	1.03	1.09	0.95	0.92
	(0.11)	(0.15)	(0.10)	(0.15)	(0.12)	(0.13)	(3.10)	(284)	(1.70)	(213)	(0.04)	(0.05)	(0.10)	(0.13)	(0.10)	(0.14)	(0.12)	(0.12)
Constant	0.74	0.02*	1.35	0.02+	59.3*	43.8+	0.01	0.00	121.1	0.00	3.3e+30	2.7e+28	2.98	0.03	0.34	0.01+	29.38	87.62+
	(1.17)	(0.03)	(2.14)	(0.05)	(122)	(92)	(0.29)	(0.00)	(4,274)	(0.00)	(1.6e+32)	(1.4e+30)	(6.03)	(0.09)	(0.68)	(0.03)	(76.7)	(235)
Observations	2,362	2,362	2,362	2,362	2,362	2,362	810	810	810	810	810	810	1,552	1,552	1,552	1,552	1,552	1,552
Age 3 Child Care Type																		
Income	0.98	1.26*	1.02	1.29*	0.79*	0.77*	0.06	1.59	15.42	24.45	0.63	0.04	1.02	1.29**	0.98	1.26*	0.78**	0.79*
	(0.10)	(0.12)	(0.10)	(0.14)	(0.08)	(0.08)	(0.16)	(3.98)	(38.29)	(61.28)	(1.58)	(0.10)	(0.10)	(0.12)	(0.09)	(0.13)	(0.07)	(0.08)
Constant	0.87	0.02*	1.15	0.03*	45.62*	39.73*	6.33e+17	0.00	0.00	0.00	2,814	1.78e+21	0.17	0.00**	5.97	0.02+	331.58**	55.54+
	(1.34)	(0.03)	(1.8)	(0.04)	(69.8)	(65.7)	(2.4e+19)	(0.01)	(0.00)	(0.00)	(108,535)	(6.8e+22)	(0.32)	(0.01)	(11.4)	(0.04)	(629)	(116)
Observations	2,328	2,328	2,328	2,328	2,328	2,328	670	670	670	670	670	670	1,658	1,658	1,658	1,658	1,658	1,658
Age 3 Child Care Type Wave 3 EITC																		
Income	1.05	1.12***	0.95	1.06+	0.89***	0.94+	1.22+	1.30*	0.82+	1.06	0.77*	0.94	1.04	1.11**	0.96	1.06	0.90**	0.94
	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.15)	(0.16)	(0.10)	(0.13)	(0.10)	(0.12)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
Constant	1.09	1.71	0.92	1.57	0.59	0.64	2.04	3.29	0.49	1.61	0.30	0.62	0.44	1.03	2.26	2.32	0.97	0.43
	(0.83)	(1.34)	(0.71)	(1.32)	(0.46)	(0.53)	(3.54)	(6.01)	(0.85)	(2.87)	(0.56)	(1.10)	(0.38)	(0.91)	(1.96)	(2.26)	(0.86)	(0.42)
Observations	2,328	2,328	2,328	2,328	2,328	2,328	670	670	670	670	670	670	1,658	1,658	1,658	1,658	1,658	1,658

Notes: All controls included in each model. FCC is Family Child Care; CBC is Center-Based Care. Standard errors in parentheses.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Income and Child Care Sequences

Figure 2.4 and Table 2.4 show results for child care sequence outcomes. In Figure 2.4, we see a strong positive relationship between income and predicted probabilities for stable formal care (i.e., center-based child care at both ages 1 and 3), and a negative relationship between increasing income and exiting formal care from age 1 to 3. The probability of enrolling in center-based care for two years ('stable formal') surpasses only one year of enrollment ('enter formal' and 'exit formal') at around $15,000 of net income, and rises above informal care in both years ('informal only') at just over $20,000 of net income.

Figure 2.4: Predicted Probabilities for Child Care Trajectories Between Ages 1 and 3.

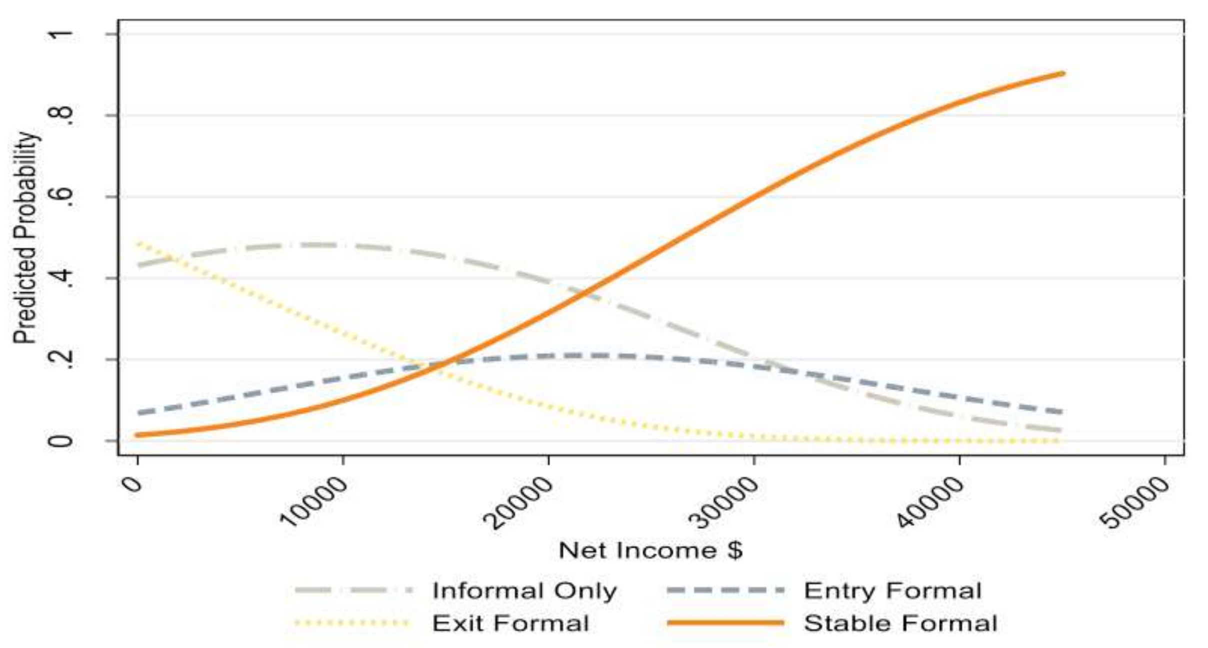


Table 2.4 presents multinomial logistic regression results for child care sequences across all households in the sample, as well as for households with one and two or more dependent children. For mothers responsible for only one dependent child, exogenous income did not impact child care enrollment patterns from child ages 1 to 3. For all mothers and those with two

or more dependent children, however, income was predictive of stable center-based child care in all relevant scenarios. In the full sample, households with $1,000 in exogenous income were, on average, 37 percent more likely to experience stable formal sequences over informal only child care arrangements than those without. These children were also 92 percent more likely to stay in center-based care from age 1 to 3 than to exit formal care at age 3. This relationship was slightly stronger for children in households with two or more dependent children. Children from families with $1,000 more exogenous income had 40 percent higher odds of exposure to stable formal care compared to informal only sequences, 94 percent higher odds of staying in formal child care between ages 1 and 3 than leaving center-based care at age 3, a 29 percent reduction in the likelihood of experiencing informal only child care compared to stable formal care, and a reduction of 48 percent in the likelihood of exiting formal care versus staying in stable formal care from age 1 to 3.

Table 2.4. Effect of income on child care sequences.

	Informal Only vs.:			Entry Formal vs.:			Exit Formal vs.:			Stable Formal vs.:		
Full Sample RRR (SE)												
	Entry Formal	Exit Formal	Stable Formal	Informal Only	Exit Formal	Stable Formal	Informal Only	Entry Formal	Stable Formal	Informal Only	Entry Formal	Exit Formal
Income	1.15	0.72	1.37*	0.87	0.63*	1.20	1.40	1.60*	1.92**	0.73*	0.83	0.52**
	(0.12)	(0.15)	(0.21)	(0.09)	(0.13)	(0.20)	(0.29)	(0.34)	(0.46)	(0.11)	(0.14)	(0.12)
Constant	0.04+	0.55	0.00***	24.36+	13.41	0.01*	1.82	0.07	0.00*	4,269***	175.22*	2,350.3*
	(0.07)	(1.80)	(0.00)	(40.66)	(46.15)	(0.01)	(5.93)	(0.26)	(0.00)	(10,353.4)	(459.54)	(8,906.9)
Obs.	2,144	2,144	2,144	2,144	2,144	2,144	2,144	2,144	2,144	2,144	2,144	2,144
One Dependent in Household RRR (SE)												
	Informal Only vs.:			Entry Formal vs.:			Exit Formal vs.:			Stable Formal vs.:		
	Entry Formal	Exit Formal	Stable Formal	Informal Only	Exit Formal	Stable Formal	Informal Only	Entry Formal	Stable Formal	Informal Only	Entry Formal	Exit Formal
Income	9.22	100.19	21.62	0.11	10.87	2.35	0.01	0.09	0.22	0.05	0.43	4.63
	(24.61)	(596.04)	(92.13)	(0.29)	(66.33)	(10.53)	(0.06)	(0.56)	(1.45)	(0.20)	(1.92)	(31.11)
Constant	0.00	0.00	0.00	3.16e+15	0.00	0.00	7.44e+34	2.35e+19	8.07e+13	9.21e+20	291,499	0.00
	(0.00)	(0.00)	(0.00)	(1.30e+17)	(0.00)	(0.00)	(6.80e+36)	(2.21e+21)	(8.33e+15)	(6.04e+22)	(20123454)	(0.00)
Obs.	601	601	601	601	601	601	601	601	601	601	601	601
Two or More Dependents in Household RRR (SE)												
	Informal Only vs.:			Entry Formal vs.:			Exit Formal vs.:			Stable Formal vs.:		
	Entry Formal	Exit Formal	Stable Formal	Informal Only	Exit Formal	Stable Formal	Informal Only	Entry Formal	Stable Formal	Informal Only	Entry Formal	Exit Formal
Income	1.13	0.72	1.40*	0.88	0.64*	1.24	1.38	1.56*	1.94**	0.71*	0.81	0.52**
	(0.11)	(0.14)	(0.21)	(0.09)	(0.13)	(0.20)	(0.27)	(0.32)	(0.44)	(0.11)	(0.13)	(0.12)
Constant	0.03+	8.98	0.00***	30.89+	277.49	0.00*	0.11	0.00	0.00**	43,017***	1,392*	386,376**
	(0.07)	(37.05)	(0.00)	(64.15)	(1,206.27)	(0.00)	(0.46)	(0.02)	(0.00)	(130,299.7)	(4,586.78)	(1,853,649)
Obs.	1,543	1,543	1,543	1,543	1,543	1,543	1,543	1,543	1,543	1,543	1,543	1,543

Notes: All controls included in each model. FCC is Family Child Care; CBC is Center-Based Care. Standard errors in parentheses.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Income and Other Child Care Dimensions

To examine whether exogenous income changes other dimensions of child care stability, I assessed the extent to which income was linked to child care multiplicity and backup arrangements at child ages 1 and 3, and total number of child care transitions between birth and age 3. These results are presented in Tables 2.5 and 2.6, respectively. Income was not predictive of child care multiplicity or backup arrangements for 1-year-olds. At age 3, however, the story becomes more complicated. Although only marginally significant, mothers with one dependent child who had received $1,000 in exogenous income two years prior were over 99 percent less likely to rely on two or more concurrent child care arrangements. In contrast, children in households with two or more dependent children were 33 percent *more* likely to experience multiplicity. Additional income resulting from EITC benefits assessed in the current year (wave 3) did not have a significant influence on age 3 multiplicity, however it was associated with increased use of backup child care arrangements to the extent of 10 percent across all households, 8 percent in households with two or more dependents, and 38 percent for single child households. Finally, results in Table 2.6 indicate that a $1,000 boost in income increased the odds of having one child care transition (versus no transitions) by 32 percent across the full sample, as well as households with two or more dependent children.

Table 2.5. Effect of income on child care multiplicity and backup arrangements.

	Full Sample	One Dependent	Two+ Dependents
Age 1 Multiplicity OR (SE)			
	Full Sample	One Dependent	Two+ Dependents
Income	1.02	1.51	0.97
	(0.18)	(5.79)	(0.17)
Constant	0.05	0.00	0.02
	(0.13)	(0.01)	(0.07)
Observations	2,295	759	1,501
Age 3 Multiplicity OR (SE)			
	Full Sample	One Dependent	Two+ Dependents
Income	1.17	0.001+	1.33+
	(0.18)	(0.00)	(0.20)
Constant	0.01+	5.08e+48+	0.00**
	(0.03)	(2.99e+50)	(0.00)
Observations	2,321	651	1,645
Age 3 Multiplicity - Wave 3 EITC OR (SE)			
	Full Sample	One Dependent	Two+ Dependents
Income	0.96	1.26	0.93
	(0.05)	(0.23)	(0.06)
Constant	0.10+	1.94	0.04*
	(0.13)	(5.16)	(0.05)
Observations	2,321	651	1,645
Age 1 Backup Arrangements OR (SE)			
	Full Sample	One Dependent	Two+ Dependents
Income	0.87	0.05	0.90
	(0.12)	(0.16)	(0.11)
Constant	1.33	7.11e+18	1.82
	(2.73)	(3.32e+20)	(4.73)
Observations	2,362	803	1,551
Age 3 Backup Arrangements OR (SE)			
	Full Sample	One Dependent	Two+ Dependents
Income	1.13	0.57	1.14
	(0.12)	(1.50)	(0.11)
Constant	0.03*	1,670.94	0.01*
	(0.05)	(66,797.13)	(0.02)
Observations	2,328	670	1,657
Age 3 Backup Arrangements - Wave 3 EITC OR (SE)			
	Full Sample	One Dependent	Two+ Dependents
Income	1.10**	1.38*	1.08*
	(0.04)	(0.18)	(0.04)
Constant	0.64	11.03	0.29
	(0.54)	(20.57)	(0.27)
Observations	2,328	670	1,657

Notes: All controls included in each model. Standard errors in parentheses.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Table 2.6. Effect of income on child care transitions.

Full Sample RRR (SE)	0 transitions vs.:			1 transition vs.:			2 transitions vs.:			3 transitions vs.:		
	1	2	3	0	2	3	0	1	3	0	1	2
Income	1.32*	0.96	1.12	0.76*	0.72+	0.85	1.04	1.38+	1.17	0.89	1.18	0.85
	(0.17)	(0.14)	(0.18)	(0.10)	(0.13)	(0.16)	(0.15)	(0.24)	(0.23)	(0.15)	(0.22)	(0.17)
Constant	0.17**	0.92	0.70	5.86**	5.40*	4.10+	1.08	0.19*	0.76	1.43	0.24+	1.32
	(0.09)	(0.57)	(0.43)	(3.22)	(4.00)	(3.03)	(0.67)	(0.14)	(0.60)	(0.89)	(0.18)	(1.04)
Observations	1,626	1,626	1,626	1,626	1,626	1,626	1,626	1,626	1,626	1,626	1,626	1,626
One Dependent in Household RRR (SE)												
	0 transitions vs.:			1 transition vs.:			2 transitions vs.:			3 transitions vs.:		
	1	2	3	0	2	3	0	1	3	0	1	2
Income	2.95	0.002+	0.11	0.34	0.001+	0.04	531+	1,568+	55.98	9.49	28.03	0.02
	(9.20)	(0.01)	(0.37)	(1.06)	(0.00)	(0.15)	(1,875)	(6,549)	(250)	(33.5)	(116)	(0.08)
Constant	0.00	1.2e+42+	2.03e+15	698227566	8.3e+50+	1.4e+24	0.00+	0.00+	0.00	0.00	0.00	5.8e+26
	(0.00)	(6.4e+43)	(1.1e+17)	(3.3e+10)	(5.3e+52)	(9.1e+25)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(4.0e+28)
Observations	573	573	573	573	573	573	573	573	573	573	573	573
Two or More Dependents in Household RRR (SE)												
	0 transitions vs.:			1 transition vs.:			2 transitions vs.:			3 transitions vs.:		
	1	2	3	0	2	3	0	1	3	0	1	2
Income	1.32*	1.05	1.24	0.76*	0.80	0.94	0.95	1.25	1.18	0.80	1.06	0.85
	(0.16)	(0.15)	(0.21)	(0.09)	(0.13)	(0.18)	(0.14)	(0.21)	(0.24)	(0.14)	(0.20)	(0.17)
Constant	0.00**	0.05	0.00+	1,900**	93.15	2.99	20.40	0.01	0.03	635.38+	0.33	31.15
	(0.00)	(0.14)	(0.01)	(4,895)	(322)	(11.2)	(60)	(0.04)	(0.13)	(2,111)	(1.25)	(125.3)
Observations	1,053	1,053	1,053	1,053	1,053	1,053	1,053	1,053	1,053	1,053	1,053	1,053

Notes: All controls included in each model. Standard errors in parentheses.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Robustness Checks

Because $\widehat{Income}_i$ is not a random variable but rather an estimated quantity, I corrected the standard errors by bootstrapping both the first and second stage together, thereby resampling the estimated quantity (Newey, 1987) as a robustness check. In Tables A1-A3 in the appendix, I present results with bootstrapped standard errors for (1) child care type at ages 1 and 3 (Table A1), (2) child care sequences from age 1 to age 3 (Table A2), and child care transitions from birth to age 3 (Table A3) across the full sample of single mothers, single mothers with one dependent in the household, and single mothers with two or more dependents in the household. Due to insufficient cell sizes, models did not converge for child care multiplicity or use of backup arrangements across most family structure types and are therefore excluded from the online appendix. Tables A1-A3 reveal identical effect sizes with occasionally attenuated levels of significance.

DISCUSSION AND POLICY IMPLICATIONS

This study extends research on the causal effect of income on parental child care enrollment patterns by using a quasi-experimental research design. Results indicate that exogenous income benefits paid through the EITC, the largest cash transfer program for low-income families in the U.S., have a significant effect on the child care arrangements made by low-income single mothers. Family income and early child care settings are highly influential in child development in ways that are likely to persist throughout a child's life, so understanding the link between the two is critical. Absent from the current literature, my focus on the causal effect of income on parental selection of child care yields insight into a policy-relevant mechanism through which supplemental family income may ultimately decrease academic inequalities among children. Grounded in the family investment perspective, this study uncovered exogenous income as a significant predictor of stable center-based child care use by low-income working mothers.

First, I hypothesized that an exogenous increase in income would increase the likelihood of choosing center-based child care over informal parental or family child care arrangements at child ages 1 and 3. I found no evidence to support the presence of income effects on child care type at age 1. This could be due to overall patterns of enrollment in child care. Despite well-established benefits, formal center-based child care is, on average, less common at age 1 than older ages (Mamedova & Redford, 2015). Indeed, among all children in the sample, 3-year-old children were twice as likely to be in center-based care than their 1-year-old counterparts. It may be, therefore, that additional measures such as effective dissemination of the important role that center-based care can play in the cognitive development and school readiness of low-income children is needed before we can see measurable income effects of center-based enrollment at age 1. Another factor to consider is that center-based child care for 1-year-olds is often substantially more expensive than center-based child care for children ages 3 or 4 (Fraga, Dobbins & McCready, 2015). As such, it could be that a larger sum of supplemental income support may be necessary to incentivize center-based child care enrollment for infants and toddlers.

As children approach school age, the benefit of early environments that promote academic preparation may be more apparent and/or accessible to parents. Indeed, my analyses suggest significant, modestly large increases (nearly 30 percent) in the probable enrollment in formal center-based child care (compared to parent or family child care arrangements) of 3-year-olds in multi-child households that received $1,000 in exogenous income measured two years prior. When using EITC transfer eligibility in the same year, $1,000 of exogenous income was indicative of a slightly lower, yet nevertheless significant increase in the likelihood of choosing center-based care relative to parent care across household composition types (multi- and single-child households). This suggests that expansions of the EITC and other work support programs that increase household income could help children from low-income families gain access to educational early environments up to two years before entering kindergarten. Prior work has linked enrollment in center-based child care over the age of 2 with enhanced cognitive benefits (e.g., NICHD & Duncan, 2003); thus increases in center-based child care enrollment at age 3 may be especially important.

Next, I found evidence to support my second hypothesis: an exogenous boost in income increases the likelihood of staying in formal child care from age 1 to 3. Specifically, in households receiving exogenous income of $1,000, children in multi-child households were 40 percent more likely to experience formal center-based care at both ages 1 and 3 than informal care in both years. Moreover, children who were enrolled in center-based care at age 1 were far more likely (about 94 percent) to remain in formal child care at age 3 than to exit to informal care arrangements. These results suggest that, in addition to encouraging enrollment in center-based child care at age 3, a policy-induced increase in income may encourage longer duration of exposure to the academic benefits of center-based child care. According to past research, two years of formal child care enrollment may have positive implications for children’s development above and beyond enrollment in only one year of center-based care (Arteaga et al., 2014).

Finally, I found minimal support for my third hypothesis that an increase in income would reduce the likelihood of child care instability as measured through child care multiplicity and backup arrangements at age 1 and 3, and total provider changes between birth and age 3. Although my findings suggest that $1,000 in exogenous income leads to a marginally significant, yet substantial decrease in multiple concurrent child care arrangements for households with only one 3-year-old dependent child, estimates for families with two or more dependents suggest an increase in multiplicity. One possible explanation for this may be the additional resources needed to make paid care arrangements for two or more dependent children compared to only one. Although average EITC transfers can produce a relatively large boost in income, the difference between the benefit amounts for one versus two or more dependents may not be enough to offset the multiple competing demands that necessitate the use of multiple concurrent child care arrangements. On the other hand, it could be that the competing demands of parental work schedules and child care (or after school care) arrangements for two or more children may be more likely to necessitate multiple concurrent child care arrangements, and additional income in fact *enables* mothers to make such needed arrangements.

Similarly at odds with original expectations, my analyses indicate that EITC benefits assessed in wave three correlate with a modest increase in the likelihood of using backup arrangements at age 3. Given that backup arrangements are typically discussed as a form of child care instability that may have negative implications for child development, my initial expectation was that, by increasing the likelihood of securing stable center-based care, mothers would have less need for backup arrangements. However, the need for special backup care when regular child care arrangements fall through may arise from spontaneous changes in maternal work schedules or other unforeseen circumstances, whereby need for some backup arrangements may be normative. In this case, additional income may also work to enable low-income single mothers to make needed backup arrangements that could otherwise be beyond their financial reach.

In terms of the number of child care transitions between birth and age 3, my analyses suggest that, at least in families with two or more dependent children, an increase in income is associated with increased chances of having one child care transition over no transitions. However, no statistically significant associations (at the $p<.05$ level) emerged suggestive of a higher or lower probability of having two or three+ child care transitions. There are a number of reasons why this might be. First, the measure of child care transitions includes transitioning into formal child care from parent or family child care arrangements. Although small cell sizes prohibited analysis of transition type in connection to increased income in the current sample, an important future line of inquiry would be to unpack the extent to which additional exogenous income may be associated with "good" versus "bad" transitions. Second, it could be that the dollar amount of EITC benefits available to parents in certain states is not large enough to purchase long-term center-based care. In this case, future study into a more nuanced dollar amount effective in shifting child care enrollment patterns could yield important insight into how we might best support uninterrupted center-based child care for vulnerable children. Second, due to unreported child care transitions between waves, or misreported counts due to faulty or incomplete recollection of events, the total number of transitions between birth and age 3 are likely under-observed, obscuring a potential reduction in two or more transitions.

Finally, it also bears noting that the effect of income on stable center-based child care arrangements was, across most measures, far more pronounced for households with two or more dependent children compared to those with only one. As indicated earlier, a likely reason for this may be because the largest EITC program impact has been found to be for families with two or more children (Dahl & Lochner, 2012). A second associated factor might be insufficient power due to small sample sizes. Of the 2,548 families included in this study, less than 35 percent reported the presence of only one dependent child in the household. On average, although coefficients did not reach statistical significance in most instances, the directional pattern of the effect of income on child care type and stability was largely the same as trajectories associated with households characterized by two or more dependent children. As such, future studies would undoubtedly benefit from larger sample sizes for comparison.

Although this study overcomes several empirical challenges by examining quasi-experimentally elicited child care enrollment patterns resulting from an exogenous increase in income, several caveats and limitations should be considered when interpreting these results. First, these findings are only applicable to low-income single-mother urban families eligible for EITC benefits. Second, my analyses are based on the assumption that single mothers claim all dependent children in the household. However, it is possible that one or more children are claimed by nonresident fathers or other family members in an effort to maximize their own tax returns. The resulting measurement error could create a downward bias in my estimates. Measurement error and biased estimates could also result from an overestimate of EITC receipt. The 2SLS IV estimations in this study relied on imputed EITC benefits to estimate exogenous household income. Although most eligible single mothers probably claimed EITC on their tax returns, is it not likely that 100 percent of them did. As a result, some mothers may have been coded as receiving EITC benefits when they did not, thereby also underestimating the true effect of income on child care type and stability.

Third, while differences across state EITC policy arenas provide a unique opportunity to evaluate the impact of exogenous income on child care arrangements, additional income from other sources may generate different effects and this possibility should be investigated. Fourth, this research does not distinguish between public and private center-based care, and child care arrangements financed through other sources such as government subsidies. This is an important limitation, because families who are able to access public center-based options such as Head Start or other free/reduced-cost preschool environments do not face the same income-driven limitations relevant to their selection of child care. Future research should take these factors into account. Finally, although the analytic sample for this study is limited to low-income mothers, a $1,000 increase in income for a single mother with a net income of $15,000 may have a considerably different effect on her selection of child care arrangements than it would for a mother bringing home $40,000. Small cell sizes prohibited analysis of income effects at different levels of net income in this study, and future research should attempt to disaggregate the effect of exogenous income at varying levels of household income.

To conclude, I present clear and robust evidence that exogenous income from EITC transfers increased stable exposure to center-based child care for low-income families. I argue that measures of state EITC and income should be standard practice in studying income effects on child care type and stability. The contribution of these data and methods to evaluate the success of income support policies most relevant to single low-income mothers is both novel and significant. Undoubtedly, future policy efforts will benefit from a better understanding of disadvantaged mothers' child care enrollment patterns and the extent to which policy-induced increases in income may result in more stable center-based child care. This study reveals that, as a means of increasing disadvantaged parents' take-home income, federal and state EITCs may be an important policy-relevant mechanism through which increased income may decrease academic inequalities among children. Given large extant disparities between low- and high-income populations, examination of mechanisms through which low-income parents may stably access center-based child care for their children continues to have great importance in population research.

Chapter 3.

Child Care Choices and Academic Achievement: The Moderating Role of Sociodemographic Structure

Abstract

Early childhood ecologies characterized by socioeconomic and sociodemographic risk are a strong predictor of poor academic achievement and lasting adversity. Stable and formal early child care settings, such as uninterrupted center-based care, can mitigate early life disadvantage. However, little is known about how various configurations of early childhood risk interact with formal versus informal child care types over time to inhibit or encourage academic achievement. Furthermore, owing to data limitations, few studies have examined these synergistic relationships over the long-term. This study links longitudinal data from the Texas subsample of the Fragile Families and Child Wellbeing Study (FFCWS) to administrative school records housed in the Texas Education Research Center (ERC) to empirically test the relationship between child care sequences from ages 1 to 3 and measures of short-, mid- and long-term academic achievement from age 3 through high school graduation, across latent subgroups of sociodemographic risk. Results indicate population heterogeneity across indicators of school readiness at ages 3 and 5, grade retention in elementary school, and math and reading achievement scores in grades 3 and 8. This innovative research approach applied to a unique dataset spanning over two decades has important implications for policy targeting interventions to children and families who may benefit most.

A growing body of research finds that early childhood education is positively associated with a host of short- to mid-term child developmental outcomes including school readiness, an important indicator of educational achievement that can translate to improved economic prospects and wellbeing later in life. As a result, many researchers, policy-makers and programs seek to positively influence rates of stable exposure to center-based educational care. However, this work is only relevant insofar as we understand the extent to which developmental gains persist, the processes through which children may benefit, the most salient outcomes across time and the extent to which certain subgroups may benefit more (or less).

In early childhood, the most influential contexts surrounding the child are the family and early care setting (Cooper & Lanza, 2014). The effects of early nonparental care on child development, however, are not homogenous across time, and are susceptible to institutional structure and organization (e.g., child care type, stability, and dosage) as well as population heterogeneity stemming from individual and family characteristics**.** Because child development is a dynamic process that takes place in multiple settings and is influenced by many factors over time (Bronfenbrenner, 1989), it is complicated to determine how child outcomes may be influenced by specific aspects of child care. We cannot assume, for instance, that the same predictors of academic achievement are relevant for all children, regardless of different individual and family dispositions, assets, and capabilities. Understanding how the effects of child care type and stability vary across population subgroups over time is important not only for disentangling how children's academic success is shaped by early childhood ecologies, but also for developing policies that effectively improve children's lives in both the short- and long-term.

Socio-ecological systems theory (Bronfenbrenner, 1989) suggests that children from disparate sociodemographic backgrounds with different constellations of individual and family risk factors may interact differently with the various dimensions of child care type and stability, which in turn can lead to heterogeneous academic outcomes. Once academic disadvantage is established by kindergarten or before, this gap frequently persists, and in many cases grows, throughout the K-12 school years (Friedman-Krauss et al., 2016). Although numerous studies examine the average effect of early child care settings on short-term academic outcomes (Magnuson & Duncan, 2016), there is a dearth of longitudinal data that concurrently tracks family background, early childhood experiences and reliable academic outcomes over time.

This study extends existing research in several ways: (1) by constructing a unique longitudinal dataset that combines early childhood ecologies and proximate family circumstances with reliable measures of educational achievement and attainment over the course of 20 years to measure long-term academic outcomes; (2) by assessing a longitudinal measure of child care type and stability to distinguish between the importance of *any* exposure and *stable* exposure to formal center-based care; (3) by addressing population heterogeneity in the effects of child care type and stability on academic trajectories that have implications for economic prospects later in life and social mobility across generations; and (4) by extending the literature on the long-term effects of stable center-based care.

BACKGROUND

The Role of Child Care Type and Stability

Outside of the family, nonparental child care is one of the most important developmental contexts for young children (Cooper & Lanza, 2014; Crosnoe et al., 2014; Johnson, 2017; Laughlin, 2013; Sandstrom & Huerta, 2013). During the developmentally sensitive period of birth to age 5, flexibility and capacity for change in brain development and skill acquisition is at its greatest, setting the stage for later advantage or disadvantage (Currie & Almond, 2011; Noble et al., 2015). Early childhood investments can therefore have a lasting influence throughout the life course. Given the significance of early childhood experiences in shaping long-term wellbeing, exposure to cognitively stimulating and developmentally appropriate child care settings can serve as a protective factor by attenuating the influence of disadvantage that can compromise healthy development (Chaudry et al., 2017). At the same time, child care settings that do not offer sufficiently cognitively stimulating educational materials, activities, and interactions can have the opposite effect, to the detriment of child development (Bigras et al., 2010; Yoshikawa et al., 2013).

Two important structural/organizational dimensions often used to characterize child care arrangements are type and stability. Nonparental care *types* can be generally categorized as formal child care, such as center-based care by licensed providers (including public preschool and Head Start), which is often referred to as early childhood education, or informal home-based care by relatives or nonrelatives (Crosnoe et al., 2014). Compared to informal settings, child care centers provide a more structured environment characterized by developmentally oriented curricula such as math and reading activities that are led by caregivers with higher levels of training and education (Dowsett et al., 2008). As a result, center-based care during infant and preschool years has been associated with better cognitive and language development and better pre-academic skills relative to home-based care evaluated on the same terms (Crosnoe et al., 2014; Dowsett et al., 2008; Duncan & Magnuson, 2013). The enhanced cognitive skills that children frequently gain through formal center-based care can have substantial effects on academic achievement and, hence, on labor market outcomes during adulthood.

Stability of early care arrangements is defined by frequency of provider changes and number of concurrent care arrangements, as well as the duration of exposure to, entry into and exit from early childhood care settings. Child care stability can be influenced in complex ways by parental need (e.g., employment and nonstandard working hours), preferences (e.g., wanting a higher-quality setting or a different type of care), constraints (e.g., income, access and cost) and supports (e.g., subsidies to help pay for care) (Crosnoe et al., 2014; Forry, Rothenberg, Sandstrom, & Vesely, 2013; Henly et al., 2015). However, researchers generally agree that multiple child care transitions and concurrent child care arrangements in early childhood create an unstable care environment that can negatively impact development (Bratsch-Hines et al., 2017; Pilarz et al., 2016; Pilarz & Hill, 2014; Sandstrom & Huerta, 2013).

Child care duration and dosage are likewise important factors of child care structure and organization that can influence child development. Not many studies have examined the extent to which contiguous exposure to center-based care (e.g., two years versus one) yields larger effects, but of the few that have, findings suggest that, among disadvantaged children, those who experience an additional year of formal care exhibit larger gains (Yoshikawa et al., 2016). Examining data from the Chicago Longitudinal Study, Arteaga et al. (2014) find that two years of CPC preschool attendance (relative to one) resulted in higher test scores in kindergarten and a reduced likelihood of receiving special education or ever being retained by 8th grade. Subgroup analyses further revealed that relative to children of mothers who had completed high school by the time the child was three, the marginal effect of a second year was greater for children whose mother had less than a high school degree. Likewise, males, who are at a greater risk for school failure among certain racial/ethnic groups, saw larger gains in reading and math scores and improving educational attainment relative to females. Insofar as early skills (often referred to as school readiness) can improve academic achievement from kindergarten to 12th grade, uninterrupted exposure to center-based child care during these influential years may, therefore, advantage certain groups of children over others.

Heterogeneity in Child Care Type and Stability Effects

Research consistently finds that greater socioeconomic and sociodemographic risk in early childhood is negatively related to children's academic achievement and competencies. Similarly, the relationship between academic achievement and child care type and stability likely varies across early childhood ecologies that differ in terms of socioeconomic and sociodemographic risk at both absolute (i.e., additive or cumulative number of risk factors) and configural (i.e., groupings of co-occurring risk factors) levels. Recent scholarship has thus demonstrated a growing interest in differential treatment analysis to discover which subgroups of children might benefit most from targeted interventions (e.g., Cooper & Lanza, 2014; Duncan & Magnuson, 2013). However, the extent to which stable center-based care differentially benefits children based on sociodemographic groupings of risk remains largely unknown.

Extensive research finds that socioeconomic factors independently predict both selection into various child care types and measures of academic achievement throughout the school years. Many families cannot afford to pay for more expensive formal care settings and do not receive public assistance to subsidize the cost. Studying a representative sample of 6,250 children born in the U.S. in 2001, Crosnoe et al. (2016) found that parents who reported needing reasonably priced child care options were less likely to choose center-based care (exclusive of Head Start). They further found that, compared to their higher-income counterparts, low-income families (<185% FPL) were significantly less likely to enroll a child in some form of center-based preschool at age 4.

Other disadvantaging sociodemographic factors, beyond economic indices of risk, can also predispose children to informal care settings. Risk factors involving family composition (Crosnoe et al., 2014), language (Yoshikawa et al., 2016), welfare receipt (Cooper & Lanza, 2014), maternal immigrant status (Cooper & Lanza, 2014), depression (Crosnoe et al., 2014), education, employment status (Coley et al., 2014; Crosnoe et al., 2016) and teen motherhood, as well as the child's race/ethnicity, early literacy and need for special education (Yoshikawa et al., 2016), can all serve as barriers to entry into formal child care arrangements. Often children from such disadvantaged backgrounds stand to benefit most from the educational inputs provided in formal child care settings, which may be lacking at home. Thus, selection into various configurations of child care type and stability can serve to further widen the gap between children who are exposed to the cognitive benefits of formal child care settings and those who are not.

A small yet growing body of literature finds that the direct effect of child care type and stability on academic outcomes can likewise vary across socioeconomic and sociodemographic lines. The theory of resource substitution posits that the beneficial effect of stable center-based care may be greater for children from more disadvantaged backgrounds with fewer alternative resources (Andersson, 2016; Magnuson & Duncan, 2016; Ross & Mirowsky, 2006). Accordingly, much of the extant literature on heterogeneity of outcomes related to early care focuses on children from low-income families, finding that children from the most economically disadvantaged families stand to gain more from formal care settings that promote academic preparation than their more advantaged peers (Coley et al., 2016; Johnson, 2017).

Other sociodemographic risk factors such as low parental education and minority race/ethnicity have also been found to differentially predispose certain subgroups of children to increased benefits of formal child care settings. Currie and Almond (2011) find that in addition to low socio-economic backgrounds, children of parents with low levels of education benefit most from formal child care attendance. Evaluating the effect of Head Start on grade repetition, among other things, Currie and Thomas (1995) found that the probability of grade repetition was significantly reduced for white children, but had no effect for black children. More recent evaluations of universal prekindergarten programs in Tulsa, OK and Boston, MA demonstrated larger marginal effects in short-term reading, math, and language skills for Asian, black, and Hispanic children, as well as English language learners (Yoshikawa et al., 2016). A separate impact evaluation of Tulsa's pre-kindergarten program in Oklahoma found that the program was more effective for children whose parents were born in Mexico (Gormley and Gayer, 2005). In terms of disparity in the persistence of outcomes, Currie and Thomas (1995) also found that, while the Head Start program evaluation revealed significant gains in test scores among both white and black children, gains among black children rapidly diminished. Thus, in terms of additional sociodemographic risk factors, the theory of resource substitution assumes that children with the greatest number of risk factors stand to benefit most from stable center-based care.

On the other hand, the concept of cumulative advantage holds that the effect of accumulating resources is multiplicative, such that child outcomes are based on the resources they bring to the table prior to the measured outcome of interest. In other words, it may be that children who enter formal care with more resources—either because of repeated exposure to early childhood education or because their parents have the capability to invest more time and/or money—stand to benefit most from formal options. The expectation of this "skill-begets-skill" model, therefore, would be that children with the least number of risk factors, as well as children with stable exposure to formal care, are in a position to reap the greatest gains from early childhood education (Cunha et al. 2006). However, by not taking a theoretical stance on the differential impact of negative environmental stimuli (e.g., informal child care settings) into account, both the cumulative advantage and resource substitution models may underestimate the aggregate effects of early care settings on academic achievement. Furthermore, very little is known about how particular *groupings* or configurations of risk (as opposed to an additive tally) may influence a child's academic trajectory.

A third, and rather underexplored, possibility is that supported by the differential susceptibility model (Belsky & Pluess, 2009), which posits that children vary in the extent to which they are affected by their early care environments. Under the assumptions of this model, the dynamic nature of risk factors at play interact in various ways, thereby exerting different levels of influence, depending on the particular configuration of risk factors that define a child's early ecology. Taking a sociodemographic background characterized by high risk, for instance, the differential susceptibility framework accounts for both the benefits of positive environmental conditions (e.g., steeper increases in academic achievement stemming from formal child care), as well as adverse effects of negative environmental conditions (e.g., lower academic achievement influenced by informal child care). The hypotheses underlying the present study borrow elements from each of these theories to explore population heterogeneity in measures of academic achievement associated with child care type and stability over time.

Present Study

Addressing current gaps in the literature, this study empirically tests the relationship between child care type and stability and children's short-, mid- and long-term academic gains in consideration of differential treatment effects across latent subgroups of sociodemographic risk.

Moderation, or subgroup analyses looking at the interaction between a main independent variable (i.e., "treatment") and a series of risk factors will often include higher-order interactions that attempt to model multiple risk factors in a single model. Such models, especially in smaller samples, are frequently limited by low statistical power. Although the combined categories of socioeconomic and sociodemographic risk being examined may be theoretically motivated, they also may not accurately reflect the actual subgroup risk profiles that tend to co-occur in the given study population. Cooper and Lanza (2014) propose latent class analysis (LCA) as a methodologically superior alternative to standard moderation analyses. As the authors explain, “a primary strength of LCA is its ability to empirically identify population subgroups based on the most common combinations of a particular set of variables” (p. 5). In line with this reasoning, the first objective of this study is to empirically identify the most common risk profiles of children in stable center-based care, and to determine which subgroups benefit more from exposure.

The second objective pertains to the analysis of long-term academic outcomes. While evaluation studies of child care programs have gained momentum over the past fifty years, estimates of long-term associations between center-based and other preschool programs and children’s later school success are limited. The existing studies on long-term effects present less consensus than the literature on short-term effects. Much of the evidence linking early childhood programs to long-term outcomes comes from two prominent experimental evaluations of small model programs that included long-term follow-ups (the Perry Preschool and the Abecedarian Project). However, these evaluations are often critiqued for a lack of generalizability to other populations (Yoshikawa et al., 2016). Furthermore, both of these studies took place before important shifts in the U.S. political climate that drastically changed the relationship between maternal employment and child care choices.

Taking advantage of a unique dataset integrating rich longitudinal data from the Fragile Families and Child Wellbeing Study (FFCWS) Texas subsample with reliable Texas state administrative school data, this study addresses the following questions:

Research Question 1: Does stable exposure to center-based child care matter for short-, mid- and long-term educational outcomes?

Research Question 2: What are the most common combinations of socioeconomic and sociodemographic risk across child care type and stability in the Texas subsample of the FFCWS?

Research Question 3: Does stable exposure to center-based care matter more for subgroups of children with different latent risk profiles, and how do these relationships persist across time?

I hypothesize that measures of long-term academic success and attainment will vary by longitudinal sequences of child care type and stability. I also hypothesize variation in long-term academic outcomes according to different subgroups of individual- and family-level sociodemographic characteristics. Hypotheses in this paper are based on the sociological theories of resource substitution, cumulative advantage and the differential susceptibility model.

Although this dataset is limited in its ability to track the long-term academic outcomes of students in the full FFCWS sample, it provides rich administrative school data and an extensive survey over two decades. Using this novel dataset and an innovative research approach, this study will contribute to a more comprehensive understanding of how early care environments shape academic achievement, which will have important implications for targeting interventions to those who may benefit most.

RESEARCH DESIGN AND METHODOLOGY

Data

To examine the effect of child care type and stability on short-, mid- and long-term academic outcomes, and assess population heterogeneity that may influence this relationship, this study capitalizes on a linked dataset comprised of rich longitudinal survey data from the Texas subsample of the FFCWS and administrative school data housed within the Texas Education Research Center (ERC) at the University of Texas at Austin.[6]

[6] To create this dataset, personally identifiable information (PII) of each mother and child participating in the FFCWS Texas survey was linked to administrative TEA and THECB identifiers. PII was destroyed by TEA prior to appending the survey data.

The FFCWS is a longitudinal multi-method cohort study of 4,898 families initially surveyed at the birth of the focal child between 1998 and 2000 in 20 U.S. cities, and followed through age 15 over six waves of data collection (focal child ages 0, 1, 3, 5, 9, and 15, respectively). The FFCWS data were collected from a stratified random sample of U.S. cities with populations of 200,000 or more and are representative of all non-marital births in large U.S. cities when weights provided within the study are applied (for additional details on sampling, see Reichman, Teitler, & McLanahan, 2001). The FFCWS study design oversamples non-marital births, wherein nearly 75% of mothers recruited to the study were unmarried. Mothers were thus more likely to be single or living with a non-biological (i.e., social) father and therefore experience higher prevalence rates of partner transitions, financial instability, and low-income status than the general population. The FFCWS is the ideal dataset for understanding the interaction between child care patterns and sociodemographic backgrounds because of the richness of measures exploring multiple facets of early childhood ecology from birth through preschool years.

Accessed through the Texas ERC repository, administrative data represent 26 years of data collected across government programs in the state of Texas. Integrating child-, adult-, and economic-level data over time to facilitate longer-term follow up of program outcomes, these data have the distinct advantage of limited attrition and far less missing data than many major household surveys.

Analytic Sample

To address the research questions outlined in this study, a novel dataset was created linking FFCWS survey data with Texas state administrative school data. From the Fragile Families data, 757 families were sampled within Texas at baseline, and a total of 810 families (mother or father and child) are recorded as having ever lived in Texas. The final analytic sample includes 685 FFCWS children successfully linked to their respective school and higher education records.[7] Given the geographic location of this subsample, Hispanic families (who tend to be heterogeneous in terms of immigration status) are overrepresented in comparison to the full FFCWS sample.

The benefit of these combined data include superior analytic capabilities than either source of data by itself. Taken on their own, ERC data are missing the rich longitudinal history of early childhood experiences included in the Fragile Families data. Similarly, FFCWS data lack the detailed and reliable educational histories of administrative school data housed within the ERC repository. Previous research has relied on good measures of one, but not the other. Linked survey and administrative data constitute a valuable means of policy-relevant research from which this study is in a position to identify more efficient and effective public policy choices that support continuous improvement for children and families.

Measures

Child Care Type and Stability

Child care type and stability over time is the primary dependent variable that is interacted with latent risk profiles to address the specific research questions of this study. Measured at the age 1 and 3 interview through maternal reports of the focal child's primary care arrangement, the series of indicator variables used to assess child care type were collapsed into three primary child care types: (1) parent, (2) informal family child care (e.g., home-based child care settings, and being cared for by a relative or nonrelative in the family's home), and (3) formal center-based care (inclusive of center-based care, Head Start, Early Head Start, and public pre-K). Children who were reportedly in care for less than 10 hours per week were coded as parent care. Child care type at age 1 and 3 were then combined to create a longitudinal measure comprised of a series of three child care sequences between ages 1 and 3: (1) *Informal Only* care in both years (this includes both parent care and family child care), (2) *Any Formal* care in either year 1 or

[7] Note, 668 mothers linked to their workforce administrative data were also requested and linked to this dataset, but are not included in the present study.

year 3 (inclusive of center-based care, Head Start, Early Head Start, and public pre-K), and (3) *Stable Formal* meaning formal care in both years. Other more complex sequences of child care type and stability were explored, for instance disaggregating parent and family child care, as well as differentiating between entrance into formal child care (formal care at age 3 but not 1) and exit from formal care (formal care at age 1 but not 3), but this rendered cell sizes of certain groups too small for analysis.

Child Academic Success and Achievement

The dependent variables of academic success and achievement were drawn from both the FFCWS and the ERC administrative database. Children's early cognitive achievement was measured at ages 3 and 5 by the Peabody Picture Vocabulary Test-Revised (PPVT-R), which assesses the size and range of words that children understand. Academic achievement in school was measured through standardized *math* and *reading* assessments administered by the Texas Education Agency (TEA) in grades 3 and 8. Given a statewide shift in student assessment implemented in spring 2012, grade 3 achievement scores were assessed through a continuous measure of performance on the Texas Assessment of Knowledge and Skills (TAKS), and grade 8 scores through the State of Texas Assessments of Academic Readiness (STAAR). Additional measures of academic achievement included a binary measure of grade repetition (1 if retained; 0 if otherwise) in elementary school (grades 1-6), middle school (grades 7-8), and high school (grades 9-12). A binary measure of high school graduation (1 if graduated; 0 if otherwise) with corresponding age of graduation was also assessed, as was matriculation into college (1 if matriculated; 0 if otherwise). College matriculation is measured by the Texas Higher Education Coordinating Board (THECB).

Latent Class Subgroups

The latent class analysis central to this study is based on a set of eight household, maternal, and child characteristics that were used to empirically identify risk profiles, or latent subgroups of children representing the presence or absence of well-established risk factors. Measured at baseline so that they preceded the process of selection into early care arrangements at age 1, household characteristics included: family structure (married, cohabiting, or single) and welfare receipt in the previous 12 months (1 if received welfare; 0 if otherwise); maternal characteristics were comprised of immigrant status (1 if foreign-born; 0 if US-born), education (less than high school, high school or equivalent, some college, or college degree or more), employment status (full-time, part-time, unemployed, or in school), teen motherhood (1 if focal child born to mother at age 19 or younger; 0 if otherwise), and depression status (1 if meets depression criteria; 0 if otherwise). Maternal depression status, measured during the age 1 survey because it is not included in the baseline survey, draws from the Composite International Diagnostic Interview-Short Form (CIDI-SF) (Kessler et al., 1998). Finally, child characteristics included race/ethnicity (white, black, Hispanic, or other) and was measured through TEA administrative records.

Covariates

Child gender, measured at baseline, was dummy-coded and included in the final models as a covariate.

Analysis Strategy

The analysis proceeded in four stages. First, children in the Texas subsample of the FFCWS were linked to their administrative school records. Second, Latent class analysis (LCA) was used to identify unobserved groupings of socio-demographic background characteristics that hang well together. Third, main effects regression and logistic models were fit to assess the extent to which child care type and stability and each latent subgroup were associated with long-term academic outcomes. Finally, using the latent classes defined in step three, moderation analysis was conducted to examine differential impact of child care type and stability on child outcomes across latent subgroups.

Stage 1: Data Linking

A study proposal was prepared and submitted to the Texas ERC, followed by review and subsequent approval by the ERC Board of Directors to conduct analyses using administrative data housed within the Texas ERC repository. Upon approval, the proposal was presented to the lead FFCWS team run by Sara McLanahan at Princeton University to devise a plan acceptable to both the FFCWS team and the ERC Director to link the data. It took roughly three months for the proposal to be processed and approved, and approximately five months for the data to be linked and released to four ERC workstations at UT Austin for analysis. I am currently the sole PI approved to access these data. Data Use and Agreement Forms were submitted to both the Texas ERC and FFCWS, FERPA and Masking trainings were passed, and an Institutional Review Board (IRB) data exemption was obtained from the University of Texas at Austin based on analysis of secondary de-identified data.

Stage 2: Identification of Latent Subgroups

Conducted in Mplus version 7.1 (Muthén & Muthén, 2012), LCA was used to assign children to latent subgroups indicated by eight categorical variables as described above. LCA is a person-centered statistical procedure that allowed for each child in the sample to be assigned to one mutually exclusive group based on observed responses to the primary variables of interest (i.e., family structure and welfare receipt; maternal immigrant status, depression, education, employment and teen motherhood; and child race/ethnicity). A one-class model was examined first, adding classes until improvements in model fit were no longer observed. Model fit was assessed using Akaike Information Criteria (AIC), Bayesian Information Criterion (BIC), and Sample-Size Adjusted BIC (nBIC), with lower values reflecting better fit. Additional model fit tests included the likelihood ratio chi-square goodness of fit test (χ^2_{LR}) the adjusted Lo-Mendell-Rubin likelihood ratio test (LMR-LRT), and the parametric bootstrapped likelihood ratio test (BLRT). A non-significant *p*-value associated with the χ^2_{LR} was indicative of absolute model fit. Comparing model solutions with *k* classes to the model solution with *k*-1 classes, significant values resulting from the LMR-LRT and BLRT signaled better fit for the more complex model solution. Entropy, with values closer to 1.0 indicating better separation between classes, was also examined. Because fit indices may often conflict or support multiple model solutions, and no single model fit index can independently determine the most appropriate number of classes, visual inspection of class profiles based on a priori theory, conceptual plausibility, theoretical interpretability, and parsimony also factored into final model selection.

Stage 3: Examination of Main Effects

Once the appropriate number of classes were selected, a new categorical designation was created and used in regression and logistic regression models (conducted in Stata version 13.1) to estimate the extent to which child care type and stability, and latent subgroups based on socio-demographic household, maternal, and child characteristics influence academic achievement and attainment. In particular, regression models were used to predict academic achievement (PPVT-R scores at ages 3 and 5, and reading and math standardized exam scores in grades 3 and 8), and logistic regression models were used to predict the likelihood of grade retention.

The following main effects models were used to estimate each dependent variable:[8]

(1) $Y_i = \beta_0 + \beta_1 CCType_i + \beta_2 X_i + \mu_i + \varepsilon_i$

(2) $Y_i = \beta_0 + \beta_1 LatentGroup_i + \beta_2 X_i + \mu_i + \varepsilon_i$

(3) $Y_i = \beta_0 + \beta_1 CCType_i + \beta_2 LatentGroup_i + \beta_3 X_i + \mu_i + \varepsilon_i$

Where Y_i represents the dependent variables (academic achievement and attainment) for child i, $CCType_i$ represents child care type and stability profiles, and $LatentGroup_i$ represents a categorical latent factor based on a series of household, maternal, and child characteristics. X_i is a row vector of demographic controls, and μ_i denotes year fixed effects to account for any variation between mean test scores for a given grade taken in different years.

[8] Note, models 1 and 2 are not presented here, but are available upon request.

Stage 4: Examination of Latent Moderation Effects

In the final stage of analysis, the influence of child care type and stability on academic outcomes was examined across latent subgroups of children.

The following moderation model was used to estimate each dependent variable:

(4) $Y_i = \beta_0 + \beta_1 CCType_i + \beta_2 LatentGroup_i + \beta_3 CCType{*}LatentGroup_i + \beta_4 X_i + \mu_i + \varepsilon_i$

Finally, to examine specific subgroup responses to child care type and stability, the data were split by latent risk subgroups and model (1) from stage 3 was estimated for each latent subgroup separately.

All models in stages 3 and 4 were estimated in Stata 13.1 (StataCorp.). To preserve cases with missing values (between 0% and 15% of the data) multiple imputations were performed. The imputation equation included all variables in the analysis, however, following von Hippel (2007), cases missing dependent variables after imputation were dropped. 20 data sets using the multivariate normal method were produced and results were averaged across these 20 data sets. National sampling weights were not used, as these are less appropriate in longitudinal analysis (Solon, Haider, & Wooldridge, 2015).

RESULTS

The key questions this study sets out to answer are: (1) what are the most common combinations of sociodemographic risk across child care type and stability profiles, (2) do stable exposure to center-based care and sociodemographic latent subgroups matter for long-term educational outcomes, and (3) does stable exposure to center-based care matter more for certain subgroups of children with different latent risk profiles. In general, my analysis found that each of the three child care profiles were predictive of academic outcomes measured at ages 3 and 5 and grades 3 and 8, as well as retention across grades 1 to 12. Similarly, the three socio-demographic classes identified through the latent class analysis were predictive of academic outcomes, however not in perfect alignment with the academic outcomes that seemed to be most influenced by child care type and stability over time.

Below I discuss the composition of each latent subgroup along with the most important patterns of association that were statistically significant at conventional (p<.05) alpha levels. Descriptive statistics by latent class membership for the sample are presented in Table 3.1. Tables 3.2 through 3.5 present results from the main effects and latent class moderation analyses discussed in further detail below. Results from the logistic main effects and latent moderation models predicting high school graduation by age 18 and matriculation into college did not yield measurable associations with outcomes and are therefore excluded from the discussion.[9] Moderation analysis for grade retention outcomes are likewise excluded due to insufficient cell sizes. Results are available upon request.

Latent Subgroups and Descriptive Statistics Across Classes

Models with one through six classes were compared, evaluating statistical indices of model fit along with theoretical plausibility and interpretability. Suggesting better balance between fit and parsimony, the three-class solution yielded the lowest BIC. Although strict interpretation of AIC and nBIC suggested marginally better fit for the six- and four-class solutions, respectively, the LMR-LRT indicated better fit for the three-class model relative to the four-class solution model. Finally, given absolute model fit based on the χ^2_{LR}, and adequate precision of classification (entropy values ranging from .775 to .797) across the three- to six-class solutions, these four plausible models were carefully examined for conceptual interpretability and parsimony. The best fitting, theoretically sound, and parsimonious model solution for this sample included three latent classes of socio-demographic risk.

The first latent subgroup, labeled *low-risk* (20.44% of the sample), was characterized by higher proportions of children who identified as white in families with married parents (at baseline) who had not received welfare in the previous 12 months (at the time of the 1-year

[9] It should be noted that, as many children in the FFCWS sample had not reached age 18 by the end of the 2018 school year, sample sizes for these outcomes were particularly small, potentially biasing estimation results. Models run following release of 2019 graduation and college matriculation data are expected to yield more robust and complete estimations.

survey), and whose mother was US-born, not depressed, had completed some college, was working full-time, and was not a teenager at the birth of the focal child. The second latent subgroup, labeled *high-risk, US-born* (68.18% of the sample), was characterized by higher proportions of children who identified as Hispanic in families with cohabiting parents who received welfare, and whose mothers were US-born, not depressed, had less than a high school degree, were unemployed, and were not teenagers at the birth of the focal child. The third latent subgroup, labeled *high-risk, foreign-born* (11.39% of the sample), was characterized by higher proportions of children who identified as Hispanic in families with married parents who did not receive welfare, and whose mothers were foreign-born, not depressed, had less than a high school degree, were unemployed, and not teenagers at the birth of the focal child.

Table 3.1 presents a description of the analytic sample by latent class assignment. Overall, the *high-risk, foreign-born* subgroup had significantly higher representation in the Informal Only profile of child care type and stability than the *high-risk, US-born* and *low-risk* subgroups (88.3% vs. 68.9% and 60.5%, respectively; p<.001). Children assigned to the *high-risk, foreign-born* subgroup were also significantly less likely to have experienced Any Formal (10%) or Stable Formal (1.67%) child care than their *high-risk, US-born* (22.7% and 8.4%, respectively) and *low-risk* (28.6% and 10.9%, respectively) counterparts (p<.01). Subgroup heterogeneity was also apparent within test scores such that the children in the *low-risk* subgroup were more likely to get significantly higher scores on the grade 3 math and grade 8 reading exams (p<.001).

Table 3.1: Descriptive Statistics by Children's Sequence of Child Care.

Latent Subgroup:	Total	Low-Risk	High-Risk, US-born	High-Risk, Foreign-born	N
Proportion of total sample, %	100.0	20.4	68.2	11.4	685
Child Care Sequence					571
Informal Only	69.2	60.5[a]	68.9[a,c]	88.3[b,c]	
Any Formal	22.6	28.6[a]	22.7[a,c]	10.0[b,c]	
Stable Formal	8.2	10.9[a]	8.4[a,c]	1.7[b,c]	
PPVT-R age 3 (mean)	87.30	97.3[a,b]	85.5[a,c]	77.4[b,c]	336
PPVT-R age 5 (mean)	93.2	100.6[a,b]	93.2[a,c]	77.4[b,c]	284
Grade 3 math (mean)	2068.1	2206.1[a,b]	2031.4[c]	2060.4[b,c]	599
Grade 3 reading (mean)	2114.8	2244.8[b]	2078.1[c]	2115.4	605
Grade 8 math (mean)	1559.5	15562.0	1563.6	1529.3	608
Grade 8 reading (mean)	1615.0	1699.5[a,b]	1594.0[b]	1598.0[c]	615
Grade Retention					
Elementary School	18.8	9.9[b]	21.1[c]	20.0	579
Middle School	5.8	1.7[b]	7.7[a,c]	1.5[b]	617
High School	24.1	13.8[b]	28.4[c]	18.0	526
Gender					685
Male	52.9	56.4	52.7	47.3	

[a]F-test and $\chi 2$ test: statistically different from High-risk, foreign-born at $p<.05$.
[b]F-test and $\chi 2$ test: statistically different from High-risk, US-born at $p<.05$.
[c]F-test and $\chi 2$ test: statistically different from Low-risk at $p<.05$.
Note: Descriptive statistics on unimputed dataset

Main Effects Models

Tables 3.2 and 3.3 presents results from main effects regression and logistic regression models (3) with year fixed effects predicting measures of academic achievement (i.e., age 3 and 5 PPVT-R scores, reading and math standardized exam scores in grades 3 and 8, and grade repetition between grades 1 and 6, 7-8, and 9-12). Overall, Children who experienced formal care at both ages 1 and 3 (Stable Formal) exhibited significantly higher scores on the age 3 and 5 PPVT-R, and grade 3 math and grade 8 achievement tests, as well as significantly lower probability of grade retention across grades 1 to 6. Latent profiles of sociodemographic risk demonstrated a persistently negative influence across indicators of academic achievement.

OLS regression models in Table 3.2 show that relative to Informal Only settings, stable center-based care (Stable Formal) was predictive of a 10.6-point increase in PPVT-R scores at age 3 (p<.001), and a 7.13-point increase at age 5 (p<.05). Grade 3 math scores associated with stable center-based care revealed a 165.23-point increase. Any Formal sequences (i.e., formal care at either age 1 or 3) were predictive of a 4.72-point increase in age 3 PPVT-R scores. Although not significant at the p<.05 level, there may be functional significance in noting (especially given the small sample size of the analytic sample) that Any Formal child care sequences maintained positive associations with grade 3 math and reading scores at the p<.1 level. Logistic regression models (Table 3.3) further revealed that stable center-based care was significantly associated with an 88% decrease in the likelihood of repeating a grade in elementary school (p<.05).

Turning to the influence of sociodemograpic risk profiles in main effects models, Table 3.2 reveals that, when compared to the *low-risk* latent subgroup, children probabilistically classified as *high-risk, US-born* could be expected to score an average of 11.8 points lower on the age 3 PPVT-R (p<.001), and 7.57 points lower on the age 5 PPVT-R (p<.001). Exhibiting persistent influence across elementary and middle school, this *high-risk* subgroup was likewise associated with an average decrease of 159.46 points on standardized grade 3 math assessments

($p<.01$) and 155 points on grade 3 reading scores ($p<.01$). Showing no significant association with grade 8 math, a reduction of 107.67 points on the 8th grade standardized reading exam could also be expected ($p<.001$). Likewise, this subgroup of children was 2.29 times as likely to repeat a grade in elementary school ($p<.05$), and 2.58 times as likely to be retained in high school ($p<.01$). Exhibiting similar, yet not as pronounced associations, the *high-risk, foreign-born* subgroup of children was associated with age 3 and 5 PPVT-R scores that were 19.68 ($p<.001$) and 22.81 points lower than their *low-risk* counterparts ($p<.001$). When taking the grade 8 standardized reading exam, these children could expect to score 106.4 points lower ($p<.05$).

Table 3.2: OLS Regression Main Effects Models Predicting Academic Achievement

VARIABLES	PPVT-R age 3 β (SE)	PPVT-R age 5 β (SE)	Grade 3 Math β (SE)	Grade 3 Reading β (SE)	Grade 8 Math β (SE)	Grade 8 Reading β (SE)
Latent Subgroup (Low-Risk)						
High-Risk, US-born	-11.7950***	-7.5733***	-159.4628**	-154.9059**	-0.2838	-107.6711***
	(2.0157)	(2.2951)	(55.6263)	(55.1092)	(33.1408)	(32.6537)
High-Risk, Foreign-born	-19.6845***	-22.8087***	-116.1607	-106.0866	-37.7447	-106.4033*
	(3.9290)	(3.6175)	(79.8996)	(79.6542)	(49.1065)	(48.6258)
Child Care Sequence (Informal Only)						
Any Formal	4.7181*	3.3154	92.2203+	109.3788+	-21.5453	-27.4596
	(1.9902)	(2.1792)	(56.0633)	(55.8934)	(34.7062)	(35.9163)
Stable Formal	10.5990***	7.1312*	165.2327*	98.3051	-25.5930	2.8086
	(2.6760)	(3.0369)	(82.9701)	(80.6997)	(55.9579)	(59.1258)
Gender (female)						
Male	-3.0808*	-1.7620	-46.7745	-77.5557+	35.9161	7.6115
	(1.5653)	(1.6769)	(42.7078)	(42.6127)	(25.5047)	(25.3021)
Constant	96.7704***	100.3165***	2,182.4604***	2,241.7582***	1,551.9661***	1,703.4289***
	(2.0558)	(2.3469)	(57.8197)	(57.3424)	(34.9570)	(35.0656)
Observations	336	284	599	605	608	615

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Differential Impact Across Latent Subgroups

Presented in Tables 3.4 and 3.5, results from moderation and within-class (i.e., latent subgroup) analyses indicated that the relationship between child care type and stability and academic achievement varied significantly across latent subgroups for all eight academic achievement outcomes with cell sizes large enough to estimate moderation models. Notably, the direction of differential impact across latent subgroups also varied across measured achievement outcomes. For the PPVT-R assessed at age 3, Table 3.4 reveals that there was a significant interaction between the *high-risk, US-born* subgroup and Any Formal care arrangements (p<.01), where further examination of within latent subgroup analysis (Table 3.5) indicated that children associated with this subgroup (unlike the other *high-risk* or *low-risk* group) were likely to incur gains upwards of 11.6 points when in stable center-based care across ages 1-3 (p<.001) and 7.92 points for children who had been placed in Any Formal care between those years (p<.001). Conditional effects displayed in Table 3.4 revealed that Informal Only care over both years was associated with a 15.46-point decrease for the *high-risk, US-born* children, and a 20.42-point decrease for their *high-risk*, *foreign-born* counterparts. Among age 5 PPVT-3 scores, Stable Formal care was associated with a nearly 7 point increase for *high-risk*, *US-born* children, but not so for any other group (p<.05). Likewise, age 5 scores were negatively associated with Informal Only care for both of the *high-risk* groups, relative to children associated with the *low-risk* latent profile. A similar pattern was found for grade 3 scores such that, relative to *low-risk* subgroups exposed to Informal Only care, the *high-risk, US-born* group was associated with a score that was 170.5 points lower on math achievement (p<.05), and 150.44 points lower in reading (p<.05). Finally, although sociodemographic risk coupled with Informal Only child care settings did not seem to exert a negative influence on grade 8 math scores, grade 8 reading scores were 141 points lower for *high-risk*, *US-born* children (p<.01), and 141 points lower for children classified in the *high-risk, foreign-born* subgroup (p<.05).

Table 3.3: Logistic Regression Main Effects Models Predicting Academic Achievement, Odds Ratios

	Elementary School Retention	Middle School Retention	High School Retention
VARIABLES	OR (SE)	OR (SE)	OR (SE)
Latent Subgroup (Low-Risk)			
High-Risk, US-born	2.2897*	3.1322	2.5752**
	(0.7880)	(2.3469)	(0.7892)
High-Risk, Foreign-born	1.9722	0.6866	1.4228
	(0.8751)	(0.8537)	(0.6317)
Child Care Sequence (Informal Only)			
Any Formal	0.7186	0.3594	1.1159
	(0.2193)	(0.2254)	(0.3043)
Stable Formal	0.1153*		0.6024
	(0.1218)		(0.2662)
Gender (female)			
Male	1.0981	1.9499	1.7721**
	(0.2378)	(0.8242)	(0.3743)
Constant	0.1294***	0.01983***	0.1151***
	(0.0456)	(0.01546)	(0.0378)
Observations	579	617	526

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Table 3.4. OLS Regression Interaction Models Predicting Academic Achievement

VARIABLES	PPVT-R age 3 β (SE)	PPVT-R age 5 β (SE)	Grade 3 Math β (SE)	Grade 3 Reading β (SE)	Grade 8 Math β (SE)	Grade 8 Reading β (SE)
Latent Subgroup (Low-Risk)						
High-Risk, US-born	-15.4609***	-8.3505**	-170.4905*	-150.4417*	15.8129	-141.0681**
	(2.4452)	(2.7788)	(71.6710)	(70.8691)	(45.3255)	(44.7583)
High-Risk, Foreign-born	-20.4229***	-24.2490***	-149.1629	-116.4608	-32.0110	-141.0755*
	(4.4757)	(4.09)	(93.3208)	(92.8932)	(58.8231)	(58.5785)
Child Care Sequence (Informal Only)						
Any Formal	-9.2316+	0.4421	97.8136	118.4528	13.4848	-97.0964
	(5.2404)	(5.9121)	(113.1859)	(111.6535)	(77.0173)	(75.8125)
Stable Formal	8.3055	(5.5593)	57.2397	89.2055	-15.8711	-50.7472
	(5.8321)	(7.4520)	(151.1903)	(151.2729)	(107.2078)	(106.293)
Subgroup*Child Care Interactions (Low-Risk, Informal)						
High-Risk, US-born*Any Formal	17.1579**	3.2177	-25.3274	-22.0719	-56.6717	87.4794
	(5.6351)	(6.4969)	(133.0169)	(130.8232)	(87.7646)	(87.5221)
High-Risk, US-born*Stable Formal	3.3073	1.4158	142.7004	7.7028	-0.1994	69.6024
	(6.6256)	(8.1969)	(181.5579)	(180.2104)	(122.2679)	(125.3877)
High-Risk, Foreign-born*Any Formal	4.2030	6.7203	142.8889	84.1490	92.7899	129.9604
	(11.3973)	(12.5646)	(236.5138)	(237.1359)	(163.3832)	(178.8203)
High-Risk, Foreign-born*Stable Formal	-3.4409	10.6023	274.3878	82.5808	-308.4052	97.3097
	(15.1255)	(16.3314)	(441.6116)	(434.9655)	(340.3704)	(309.4583)
Gender (female)						
Male	-2.9678+	-1.8312	-45.259	-76.4248+	39.3932	8.7242
	(1.5671)	(1.7002)	(43.1613)	(43.0558)	(25.7371)	(25.5572)
Constant	99.4921***	101.0686***	2194.173***	2239.577***	1538.024***	1731.091***
	(2.3529)	(2.7124)	(68.0943)	(67.4918)	(43.8021)	(43.4130)
Observations						

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Table 3.5(a). OLS Regression Models Predicting Academic Achievement Across Latent Subgroups

	PPVT-R age 3			PPVT-R age 5		
	Low-Risk	High-Risk, US-born	High-Risk, Foreign	Low-Risk	High-Risk, US-born	High-Risk, Foreign
VARIABLES	β (SE)	β (SE)	β (SE)	β (SE)	β (SE)	β (SE)
Child Care Sequence						
Any Formal	-9.0840	7.9192***	0.7210	0.2941	3.6570	8.7371
	(6.3268)	(1.9927)	(10.0903)	(5.6279)	(2.3539)	(16.5949)
Stable Formal	7.4386	11.6314***	-0.8792	5.0284	6.9756*	14.0769
	(7.3554)	(2.8431)	(12.9329)	(7.1418)	(3.2941)	(22.1847)
Gender (female)						
Male	-5.4610	-3.1521+	11.1008	-3.7641	-1.7820	1.9234
	(4.6338)	(1.6531)	(7.1235)	(4.0489)	(1.8483)	(9.6504)
Constant	100.8747***	84.1297***	72.8674***	102.2369***	92.6940***	75.1497***
	(3.7195)	(1.3522)	(4.8245)	(3.4240)	(1.4435)	(6.4878)
Observations	63	256	17	46	215	23

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Table 3.5(b). OLS Regression Models Predicting Academic Achievement Across Latent Subgroups

	Grade 3 Math			Grade 3 Reading		
	Low-Risk	High-Risk, US-born	High-Risk, Foreign	Low-Risk	High-Risk, US-born	High-Risk, Foreign
VARIABLES	β (SE)	β (SE)	β (SE)	β (SE)	β (SE)	β (SE)
Child Care Sequence						
Any Formal	102.5638	72.6915	324.9952+	119.6475	96.4119	300.3182
	(100.3317)	(71.4903)	(188.9815)	(101.5340)	(70.6299)	(190.7812)
Stable Formal	55.1920	199.1840+	291.3294	88.3834	96.5435	123.3319
	(133.5712)	(108.2837)	(352.5060)	(137.4110)	(103.4685)	(347.1706)
Gender (female)						
Male	-82.0514	-64.8270	142.4942	-88.5366	-107.0863*	141.4931
	(87.0248)	(54.1305)	(112.8292)	(88.5760)	(53.7328)	(113.6210)
Constant	2,212.4445***	2,033.7455***	1,950.8099***	2,245.7554***	2,105.0040***	2,013.8348***
	(71.4473)	(42.8911)	(80.6423)	(73.4584)	(42.7387)	(81.6480)
Observations	114	413	72	117	416	72

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Table 3.5(c). OLS Regression Models Predicting Academic Achievement Across Latent Subgroups

	Grade 8 Math			Grade 8 Reading		
	Low-Risk	High-Risk, US-born	High-Risk, Foreign	Low-Risk	High-Risk, US-born	High-Risk, Foreign
VARIABLES	β (SE)	β (SE)	β (SE)	β (SE)	β (SE)	β (SE)
Child Care Sequence						
Any Formal	9.1504	-42.6698	106.4451	-91.9372	-10.3041	33.1040
	(90.3537)	(39.0637)	(127.9069)	(74.8931)	(44.5048)	(156.0970)
Stable Formal	-10.8063	-16.1562	-324.6237	-55.5180	18.9551	45.3208
	(127.9038)	(63.5854)	(299.8599)	(104.5842)	(72.2392)	(245.8869)
Gender (female)						
Male	89.2623	26.2299	38.5703	-54.2593	25.7426	10.1201
	(72.8212)	(29.1572)	(67.6189)	(56.9591)	(31.2895)	(67.1387)
Constant	1,511.3250***	1,560.5437***	1,506.4520***	1,765.7079***	1,581.3575***	1,589.3775***
	(63.2149)	(23.1052)	(49.7889)	(50.7539)	(25.2357)	(51.5567)
Observations	116	425	67	120	427	68

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

DISCUSSION

The link between exposure to nonparental care in early life and short-term academic achievement is well documented, and scholars agree that children who attend center-based child care enter school better prepared to learn (Dowsett et al., 2008). Research on the long-term benefits of early child care, however, is inconclusive. Furthermore, research has just begun to examine the extent to which a child's sociodemographic background conditions the association between stable center-based care and academic achievement. To accurately measure the influence of child care on the academic achievement of children from different backgrounds, research questions and data analysis must account for the environments within which the child is embedded (Votruba-Drzal et al., 2004).

Analysis of heterogeneous distributional effects can provide a more complete picture of how child care ecologies affect subsequent development, and how policy might intervene to best serve the needs of diverse low-income families. Roughly three out of every four children aged 3 to 5 in the U.S. experience some form of regular nonparental care before entering kindergarten (Corcoran & Steinley, 2017). Consequently, understanding the ways in which child care is linked to academic achievement can help support efforts to promote child development and reduce disparities in school readiness and beyond.

The present study adds to the literature on child care by assessing the role of type and stability in shaping children's academic outcomes from pre-academic skills through high school graduation. Using data from the FFCWS linked to administrative school records in Texas, this study extends prior research in three important ways. First, the construction and use of linked survey and administrative data spanning more than two decades provides necessary analytic depth for examining longer-term educational outcomes lacking in prior research. Second, a longitudinal measure of child care type and stability is examined to determine whether it is any exposure to formal care or stable exposure to formal care that matters most for children's academic trajectories. Notably, this measure directly addresses child care dosage, an important yet understudied element of child care that has clear implications for child care policy. Third, population heterogeneity is addressed by examining how the relationship between stable center-based care and academic achievement differs across subgroups of children with different latent risk profiles.

Persistence of Main Effects Over Time, Stability/Dosage, and Risk Profile Groupings

Evidence of a persistent child care influence beyond grade 3 is not found across nine indices of academic achievement. Although highly influential for early measures of achievement (e.g., age 3 and 5 PPVT-R scales), the positive influence of formal child care in the presence of sociodemographic risk did not extend to grade 8 math and reading scores or high school grade retention. In terms of stability/dosage, of early care, however, measures of academic achievement were consistently larger and more positive in response to Stable Formal care compared to Any Formal care at age 1 or 3. Although more research is needed for conclusive evidence, this finding has important implications for policy formation. State governments across the nation have either implemented, are considering implementing, or have been approached by lawmakers with funding proposals for universal and need-based pre-kindergarten programs to support the healthy development of young children. Given the cost of publicly funded early childhood education programs, policy-makers will have to work through a cost-benefit analysis when deciding between options to expand access of single-year programs to more children versus allocating limited resources for a second year that will likely target a smaller and more disadvantaged group of children. Findings in support of resource substitution (e.g., disadvantaged populations stand to reap the largest gains from early intervention) suggest that preschool programs that offer targeted services over two years may be a more efficient and effective way to allocate limited public funds.

The negative reach of sociodemographic risk, on the other hand, was evident in measures of academic achievement throughout high school. Interestingly, relative to the *low-risk* subgroup, children associated with the *high-risk, US-born* group seemed to fare worse than the *high-risk,* *foreign-born* group in most measures of academic achievement. Although both *high-risk* subgroups exhibited poorer outcomes relative to the *low-risk* subgroup, both groups were characterized by Hispanic minority identification, less than a high school degree, and unemployment. The major compositional distinctions between these two *high-risk* groups were: welfare receipt (with the *US-born* group exhibiting greater likelihood of receipt), country of birth, and cohabiting (*US-born*) versus married (*foreign-born*) groups. Although marriage tends to confer a relative advantage over cohabitation (and certainly single-motherhood) in terms of overall family structure, research tends to find comparatively little to no substantive differences between cohabitation and marriage among mothers of Hispanic descent. Thus, in an additive sense, each of these subgroups can be characterized as encompassing an "equal number" of risk factors. These findings therefore lend support to the idea that the influence of sociodemographic risk is not based solely on the additive impact of risk indices, but rather the particular configuration of risk factors taken together.

Population Heterogeneity

Overall, this study finds that child care type and stability function differently for children associated with different latent risk profiles. Across multiple indices of academic achievement, moderation analyses exhibited support for the differential susceptibility model. For instance, across age 3 and 5 PPVT-R scores of early cognitive achievement, as well as grade 3 math achievement, benefits incurred from formal child care, and especially stable center-based care, were stronger and more positive for children classified as *high-risk, US-born*. Meanwhile, conditional effects evident in the interaction models suggest that Informal Only child care sequences (considered negative inputs in this context) were consistently worse for both *high-risk* subgroups in terms of academic achievement measured through the age 3 and 5 PPVT-R, grade 3 math, grade 3 reading (although results were significant only for the *high-risk, US-born* subgroup), and grade 8 reading. Finally, although not significant at the $p<.05$ level, it is worth noting that Any Formal care exhibited patterns of negative influence on age 3 PPVT-R scores for the *low-risk* subgroup, further suggesting that the effects of child care type and stability may depend both on population subgroup composition, as well as the outcome being studied.

Limitations

This study has several limitations. First, despite the rich nature of these combined survey and administrative data spanning over 20 years, the limited sample size constrained analytical power needed for reliable prediction among certain subgroups of children. For instance, most significant within-class findings were found among the *high-risk, US-born* subgroup, which was also by far the most highly populated subgroup, accounting for nearly 70% of the entire sample. Future research should aim to obtain larger panel data spanning childhood through young adulthood to substantiate the findings of this study. Second, in the absence of experimental (or quasi-experimental) methods applied to a nationally representative sample, both internal and external validity are compromised. In addition to dependence on the constellation of risk factors specific to the given sample for the construction of latent subgroups, the current analytic sample is further influenced by additional structural factors such as geographic location (e.g., yielding overrepresentation of Hispanic families), and therefore cannot be generalized beyond those types of at-risk populations. For instance, when latent classes were estimated in the full FFCWS sample, the configuration of empirically correlated risk factors and proportions of children classified into each latent risk subgroup differed substantially from the current sample, and would undoubtedly differ across other representative samples. Finally, given gap years in measurement of child care type and stability inherent in the FFCWS study design, full coverage of early child care exposure is almost certainly lacking. Reliance on maternal reports of child care type and transitions at only two points in time to assess early child care experiences are expected to result in the underestimation of child care transitions present within the sample. Although data limitations are par for the course in population research, future research on this topic should strive for a more complete conceptualization and measurement of child care type and stability.

Conclusions

These findings contribute to a growing literature on the academic correlates of stable center-based care, as well as the differential influence of child care type and stability. This study helps to better understand the patterns of influence stemming from stable center-based care that can be linked to longer-term academic outcomes. Taken together, findings from this innovative research approach applied to a novel dataset underscore the importance of population heterogeneity for a better understanding of the association between child care type and stability and academic achievement, and have implications for targeting interventions to those who may benefit most.

Chapter 4. Conclusion

Although child poverty is a result of many social and economic forces, public policy can play a role in increasing family resources and reducing the risks associated with poverty. Given the stakes involved in closing persistent income-based achievement gaps, the links between these gaps and parental investment in time and expenditures, and the evidence that some specific early interventions are associated with shrinking achievement gaps, a major effort aimed at equalizing resources and quality child care options for children ages 3 and younger should be a primary part of any major national investment in America's children.

This dissertation sought to understand a number of policy-relevant objectives: (1) the child care needs of diverse low-income families, (2) economic factors that play a role in parents' decisions about child care, (3) issues related to the participation of various groups in different types of early care and education programs, (4) school-level processes and outcomes that might be influenced by child care, (5) how school-level processes and outcomes that might be influenced by child care may vary by certain groups of children, and (6) the strength in using integrated data systems to discern patterns of exposure and resilience.

To address these objectives, this dissertation drew on data from a large representative household survey, the FFCWS, as well as Texas administrative school data. This research has important implications for the potential to coordinate work support policies that address income with early intervention efforts to produce the greatest benefit for children. The policy-relevant solutions, in this case, might be to encourage parents to use stable center-based care by bolstering, or expanding, work support and other safety-net policies that address income, and using integrated data systems to track the effects of early childhood programs on diverse subgroups of children over time.

KEY FINDINGS

Overall, I found that a difference of $1000 in family income increases the likelihood of exposure to formal center-based child care between the ages of zero and 3, wherein these early exposures may have measurable academic impacts for certain groups of children lasting through elementary school.

In chapter 2 I found that a $1000 difference in income was predictive of being more likely to enroll in center-based care over remaining in parent care or being placed in family child care at age 3. Likewise, a $1000 difference in income was predictive of being more likely to experience stable formal child care over informal only care sequences or starting in formal care at age 1 and exiting to informal care at age 3. Overall my findings suggest that an exogenous boost in income precipitated by an EITC transfer increases the likelihood of enrollment in stable center-based care for children raised in low-income families.

In chapter 3 I found that, compared to children associated with low-risk profiles, children in either high-risk group fared worse on measures of academic outcomes ranging from school readiness at ages 3 and 5, and lasting through the 8th grade math and reading scores. In line with these results, children in the high-risk, US-born group were upwards of twice as likely to be held back in elementary and high school. Controlling for sociodemographic risk, any formal, and stable formal child care resulted in higher achievement scores from age 3 through the third grade, while children who experienced stable formal child care were 88% less likely to be held back in elementary school. Exposure to any formal, and especially stable formal child care arrangements between ages 1 and 3 may serve as a protective factor for children whose characteristics resemble the high-risk, US-born profiles through grade 3, and, in the case of third grade math scores, children who were associated with high-risk, foreign-born profiles.

These findings indicate that formal center-based child care can have positive effects on child academic outcomes through elementary school and, for certain groups, through middle school. Moreover, formal child care arrangements, especially when experienced across multiple years in early childhood, may serve as a protective factor for children characterized by multiple sociodemographic risk factors.

SYNTHESIZING FINDINGS

To the extent that a policy-induced increase in income may lead to increased exposure to center-based child care for poor and low-income children, this dissertation points to an additional mechanism by which government economic support can positively influence academic outcomes and lifelong wellbeing among disadvantaged children.

The theoretical underpinnings of the second chapter of this dissertation suggest that greater income may promote conditions necessary for young children to thrive through access to nurturing, responsive, and safe early childhood settings found in formal child care centers. To my knowledge, there are no causal studies that have attempted to empirically justify this claim. The empirical findings presented in this dissertation provide preliminary and novel evidence in support of this pathway. Thus, insofar as findings from chapter three support and build upon the literature on the association between formal center-based child care and cognitive and academic outcomes, the combined findings of this dissertation highlight policy, and in particular the EITC, as a potential mechanism for longer-term academic outcomes fostered through access to enhanced early childhood learning environments for poor and low-income families.

Taken as a whole, the empirical findings of this dissertation help to clarify both where and how work support policies such as the EITC can make a significant impact. Children growing up in impoverished and low-income families are at risk for less optimal physical and mental wellbeing, compared to their wealthier counterparts. Moreover, as discussed in chapter 1 as well as both empirical chapters, these lasting socioeconomic disparities take root in the earliest years of childhood. By increasing the incomes of poor and low-income working families when children are between the age of zero and 3, federal and state EITC benefits can improve early childhood settings and thereby the developmental trajectories and lifelong health of economically disadvantaged children.

CONTRIBUTIONS

The design of the two empirical studies that comprise this dissertation had the benefit of testing multiple sources and combinations of variable support levels and population heterogeneity (e.g., state tax credits of varying amounts and differing combinations of sociodemographic risk) using both population and linked data. These design elements provide an additional layer of detail not found in other studies that may yield a more nuanced understanding of the potential levers of change and targeted interventions available to policymakers. This dissertation addressed important questions about the interplay between income, work support policies, and context in shaping the wellbeing of children today and in the future. Findings from this dissertation yield important insight regarding the relationship between income, income support policies, and school-level outcomes through dimensions of child care.

In particular, the first Aim extends the body of research on the causal effect of income on parental child care decisions by using a quasi-experimental research design. Family income and early care settings are highly influential in child development in ways that are likely to persist throughout a child's life. Understanding the link between the two is therefore critical. Absent in the current literature, a focus on the causal effect of income on parental selection of child care yields insight into a policy-relevant mechanism through which supplemental family income may decrease academic inequalities among children. Findings from this study will provide valuable information for policymakers and researchers interested in the intersection of anti-poverty work supports for improving child development and wellbeing over the life course.

To my knowledge, the second chapter of my dissertation is the first paper to measure the effect of income on patterns of child care use among low-income families using quasi-experimental methods. Through this work, I also extend the limited body of research on predictors of child care use, and I highlight the importance of intermediate outcomes. This study further identifies and gives insight into a policy-relevant institutionalized mechanism by which supplemental family income can encourage stable center-based child care. Finally, by examining heterogeneity by state-level policies, this work also shifts the thinking of child care as a purely family-level “choice,” to one where government and policy have a more prominent role.

From a theoretical standpoint, this work helps elucidate and advance the knowledgebase of how a policy-induced boost in income might influence decision-making of low-income parents through increased access to more optimal early childhood settings such as formal center-based child care. Lacking in prior literature, chapter 2 provides preliminary empirical support for the theoretical link between income precipitated by the EITC and exposure to center-based child care. In particular, increasing the availability of resources (i.e., income) removes barriers to parental investment decisions by increasing access to formal child care settings. In short, greater income can promote access, and therefore increased exposure, to center-based child care.

To address Aim 2, I created a novel dataset linking extensive survey and administrative school data in Texas. This study made the following contributions: first, by linking rich survey and robust administrative longitudinal data, I add to a growing body of literature that recognizes the importance of integrated data systems in enumerating important patterns and relationships across systems. Second, I extended the literature on the influence of stable center-based care by estimating its long-term effect on academic achievement and attainment. Third, I took advantage of this unique and novel dataset to examine differential effects of child care type and stability over time and across children from different sociodemographic backgrounds. This work therefore has important implications for targeting interventions to those who may benefit most.

Finally, this innovative research approach adds to the scientific literature by contributing to a more comprehensive understanding of how early care environments shape academic achievement. In the third chapter of the dissertation I highlight not only the importance of sociodemographic factors in the differential impact of early child care arrangements on academic outcomes, but also the clustering of sociodemographic risk in this population heterogeneity. Although the theory of differential susceptibility helps to explain why many of the academic benefits of center-based care were associated with higher-risk child profiles over the low-risk group of children, this work points to important gaps that should be addressed. In future work I will attempt to further disaggregate why the strongest academic benefits stemming from formal center-based care materialized for US-born groupings of high-risk children as opposed to foreign-born high-risk profiles.

LIMITATIONS

Chapter 2

As with most observational and experimental studies, we know that the findings presented in this dissertation are not generalizable to different populations beyond the specific sample used for each study. In chapter 2, my findings are only applicable to low-income single-mother urban families eligible for EITC benefits. More importantly, however, is the issue of bias.

It could be that others, such as a noncustodial father or another relative, may be claiming dependent children in the household in an effort to maximize their own tax returns. If this is the case, the EITC benefit amount reported by the TAXSIM program would indicate eligibility for a higher benefit amount than a mother not claiming a child would in fact receive. Similarly, because the EITC amount I use as my instrument is based on credit eligibility as opposed to actual receipt, it is likely that my model overestimates the number of mothers who actually received the credit. In both of these scenarios, however, my findings would represent an underestimation of the true effect of income on child care enrollment patterns. As such, this may in fact serve to bolster my study findings.

It is also possible that income resulting from other sources may generate different effects from income based on the EITC. As mentioned in chapter 2, the EITC is received as one lump sum. As child care payments are typically due on a monthly basis, it could be that additional income received in monthly increments may give mothers more flexibility in how they decide to spend that money, and perhaps serve to further encourage spending on center-based child care. Future research should endeavor to examine the effect of additional safety net policies that address income, as well as other sources of income that may influence patterns of child care enrollment. Insufficient sample sizes were also somewhat problematic in this study. For instance, due to small cell sizes, I was not able to disaggregate the effect of an exogenous boost in income at different levels of net income. However, it is quite likely that $1000 of additional income for a mother making $10,000 would lead to different spending patterns than $1000 of additional income for a mother making $40,000. This study should therefore be replicated using larger nationally representative datasets.

Finally, an issue that is left unaddressed in this work is the price effect that may be influenced by the child care subsidy program. Beyond the income effect that is addressed at length in this dissertation, the price effect is influenced by the fact that some families in my sample received child care subsidies (thereby encouraging the use of center-based care by making it less expensive), and some did not. The child care subsidy program is a means-tested, state-run program that helps low-income families pay for child care in a variety of settings, including licensed child care centers and homes, as well as some unlicensed settings. Specific federal eligibility requirements include work, education, or training mandates for adults in the household, and a household income of less than 85% of the state median income (Child Care and Development Fund, 2019). Not all eligible children benefit from child care subsidies, however, and eligible populations served vary across states. For instance estimates of the proportion of eligible children who are served by the program vary between 15-20 percent (Shanks & Danziger, 2010). Because some families in my sample received child care subsidies and some did not, this study does not acknowledge the fact that parental investment decisions to enroll their child in center-based care may have been the result of a child care subsidy for certain families. Furthermore, in addition to low (and therefore inconsistent) subsidy receipt among eligible families, 85% of the average median income between 1999 and 2003 comes to a little under $37,000, thereby excluding the portion of my sample with household incomes between $37,000 and $45,000. This introduces a potential endogeneity problem that needs to be addressed in future work.

Chapter 3

In chapter 3, my findings are only applicable to Texas residents who participated in the Fragile Families study. Furthermore, the limited sample size resulting from using only one of 15 states included within the full data constrained analytical power needed for reliable prediction among certain subgroups of children. Having substantial diversity in the sample is critical and in the sample sizes of the racial/ethnic groups in particular. Future research should aim to obtain larger panel data spanning childhood through young adulthood to substantiate the findings of this study. It is also important to note that, in the absence of experimental (or quasi-experimental) methods applied to a nationally representative sample, both internal and external validity are compromised. More work will be needed to examine robustness of findings and consider intercorrelations between other sociodemographic factors.

FUTURE DIRECTIONS

Near-Term

Chapter 2

There are a number of near- and far-term analyses that will come directly from this dissertation. In the near term, the issue of the employment effect in my second chapter will be addressed through two separate robustness checks. First, I will limit the analytic sample for this study to mothers who were working during the age 1 survey. This helps to address the employment effect because these mothers were already working, and thereby not incentivized by the EITC to enter the labor force, which would increase their need for non-parental child care. In essence, because this cohort of single mothers all have a need for non-parental child care, the question then becomes one of: among working mothers, does a difference in income precipitated by the EITC encourage take-up of formal child care arrangements versus informal arrangements. Although results I present in this dissertation are not from this restricted sample, my initial findings yield similar results.

Limiting the analytic sample to working mothers does not, however, account for mothers moving from part- to full-time work, or vice versa, as a result of incentives (or disincentives, as the case may be) stemming from federal and state EITC benefits. To further address the employment effect, therefore, I will construct a simulated instrument based on the average state EITC amount for a family given geographic location, year, and family composition. Because EITC benefit amounts will be based on aggregate state averages, this will take care of endogeneity issues caused by the fact that the EITC may not only increase work, but also work hours of a given mother.

Chapter 3

Looking towards near-term work for my third chapter, I am excited to be granted remote access to the data in mid- to late-August in order to continue my work outside the confines and restrictions presented by COVID-19. Prior to research interruptions in March 2020, I was in the process of linking additional data years that had become available in order to more accurately track high school graduation and college matriculation within the full sample of linked data. In light of these new data, I will write a second manuscript looking at the association between early childhood care arrangements and longer-term outcomes including high school graduation, SAT/ACT-taking and scores, and college matriculation. For this near-term novel manuscript, as well as the one that will result from chapter 3, it will be important to present my findings in standardized effect sizes using state-level averages and standard deviations.

Long-Term

In the longer-term, in addition to replicating results from chapter 2 with comparable datasets such as the ECLES-B and the SIPP, I would like to look at how exogenous income may affect additional outcomes such as teacher reports of behavior in elementary school, measures of parental and school connection, as well as other important measures of mental and physical health. With age 22 data being currently collected by the Fragile Families team, I am also excited by the prospect of eventually examining various early-adulthood outcomes, as well as linked age 22 and Texas Workforce data available through the Texas ERC.

Finally, I will further build on this body of work and leverage new opportunities to enhance evidence-based policy in two key ways. *First*, the federal devolution of power has created diverging policy contexts across states, and this has implications for population health and wellbeing. The same is true of nation states abroad. I plan to use restricted data from multiple nationally representative and complex datasets in the U.S., Europe, and beyond to examine how social safety nets shape the consequences of early life disadvantage. For example, the association between early childhood poverty and human capital development or health may be weaker in states with strong social safety nets. Furthermore, the timing and packaging of social welfare policies may vary depending on the sociopolitical climate of a given state or country. In this work, I will also expand my unit of analysis to examine the population and health consequences of social programs and policies such as maternity leave and unemployment benefits. I will build on theories of parental investment, human capital and health to suggest that state policies and policy bundles are an important contextual factor.

Second, I am a strong proponent of integrated data systems for the social sciences. I believe large datasets linking various strands of administrative data, as well as those linking survey and administrative data, to be the future of population research, and, much like my work linking administrative and survey data in Texas, I intend to be at the forefront of this movement. I will extend my work linking survey and administrative data to expand larger-scale integrated data structures that encompass the entire family to track social inequalities and policy change over time. As I look ahead, I would be interested to pursue a research alliance with various states to institutionalize integrated, comprehensive data systems across the U.S. and beyond. The hypothetical cost effectiveness of interventions is greatest when targeted to those who need it most. The advent of integrated data systems, including large-scale linking of administrative data, holds great potential for tracking and analyzing the disparate effect of social policies across diverse populations and states. Identifying population subgroups that may benefit most (or least, as the case may be) from early childhood interventions and exposures across states and policy contexts helps highlight and target potential areas for intervention.

I will therefore build on my current work to explore the extent to which sociopolitical and institutional determinants (i.e., policy interventions) of emotional, behavioral, cognitive, and physical health outcomes vary across data contexts. I also intend to move towards the inclusion of predictive analytics to supplement our current knowledge base and inform future policy decisions and sociopolitical discourse. To pursue this work, I plan to lead and contribute to writing major grant applications for submission to external funders and publish in internationally renowned peer-reviewed journals. In line with my prior work, these future projects will continue to examine nonlinear and understudied trajectories that characterize the dynamic and synergistic relationship between social policy, human development, and population health.

POLICY AND PRACTICE

The implications for policy and intervention that come from this dissertation are three-fold. First, this work echoes the rapidly growing science of adversity and resilience and underscores the urgency for early intervention to prevent ecological adversities that can (and so often do) lead to problems in early learning, social-emotional development, and both physical and mental health across the life course. Second, since policy priorities (and, unfortunately, funding streams) are unlikely to change overnight, expanding existing income support policies such as the EITC, which has a preexisting political infrastructure and track record of broad success and bipartisan support, may prove particularly effective, especially in light of the extreme challenges of 2020 that call for immediate action. Third, by taking strides to mainstream the use of linked household survey and administrative data, as well as integrated administrative data systems, social scientists will be better able to identify population subgroups at risk for suboptimal development that stand to gain the most from early intervention and design targeted interventions and programming that stand to make the greatest impact.

As highlighted in chapter 1 and throughout this dissertation, supporting children in the prenatal to age 3 period can help build a strong foundation for lifelong health and wellbeing. By understanding how early adversity can affect later development, and what we can do about it, we can reignite the urgency for early childhood investment in a peri- and (hopefully soon) post-pandemic world. We must use advances in the science of the developing child to inform proposals (including, as necessary, design, evaluation, and scaling) for early intervention strategies that are practicable and actionable. In this dissertation, I argue that one of the most immediate areas of focus must be around increasing family income, which has the direct benefit of allowing for better child care options.

The first actionable policy recommendation, then, is to expand the federal and state EITC program to reach a wider swath of families and provide greater levels of financial assistance. This can be done by expanding the EITC schedule for the lowest earners (i.e., increasing payments along the phase-in and flat regions starting at $1 of earned income) and increasing the generosity of payments across the entire schedule (i.e., the phase-in, plateau, and phase-out regions of the credit). Expansion of the EITC would help alleviate many of the negative correlates of early life economic disadvantage by directly supplementing the household income of low-wage parents, or by encouraging work, likewise increasing household income of low-earning parents. Based on the parental investment theory, this increase in household income would allow low-income parents to invest in their children's human capital by, for instance, enrolling them in formal center-based child care.

Speaking to the practicable nature of this proposal, in addition to being widely acknowledged as the largest poverty alleviation program in the United States, the EITC generally enjoys bipartisan support (NASEM, 2019), as well as an existing political infrastructure that would not require much more than the allocation of additional funds to expand the program. In other words, there would be no need for novel program design and pilot testing that require more resources and, importantly, time arguing over new programming. Although I support constant growth and innovation in policy solutions aimed at helping our most vulnerable populations, novel policy ideation and implementation can detract from more rapid, and perhaps immediately effective, policy solutions needed to face the exponential growth of economic crisis we face in 2020.

Although not as widely popular and readily accessible as the EITC, child care subsidies through the Child Care and Development Fund (CCDF) and the Child Care and Dependent Tax Credit represent two additional work support policies through which income and exposure to center-based child care among low-income families could be increased. Authorized under the Child Care and Development Block Grant Act (CCDBG), the CCDF (which represents the primary source of federal funding for child care subsidies for low-income working families) should be transitioned from a partially-funded block grant program to an entitlement system whereby all eligible families are able to access the credit. In addition to a substantial increase in federal spending on child care assistance, addressing the clear shortcoming of income eligibility limits of current child care subsidies would further require limiting the vast flexibility that states have to set specific program rules for how the CCDBG funds are distributed (Bivens et al., 2016). Another mechanism through which low-income families could gain access to center-based child care through a policy-induced boost in income is the child and dependent care tax credit (CDCTC). Through the CDCTC, two-parent households where both parents are employed can receive a tax credit of up to $2,100. The issue with the CDCTC is that it provides minimal to no benefit to low-income families because it is non-refundable, meaning only families making enough income to owe taxes can actually receive it (Bivens et al., 2016). A plausible solution, therefore, would be to make the CDCTC refundable, which, according so some estimates, would make the benefit available to over one million additional families (Rohaly, 2007).

Finally, there is increasing interest in the use of linked household survey and administrative data, as well as integrated administrative data systems, for data-driven research and policy taking hold across social and population sciences. A second, albeit longer-term, policy proposal involves a concerted effort to link administrative data across systems at all levels of government—federal, state, and local agencies of all sizes. Building a data infrastructure to support the use of government data across administrative systems to track program performance and measurable outcomes would advance social science research and policy innovation.

For instance, direct measurement of key indicators of child health and development could enhance clinical innovation and management and help secure payment for effective services. Credible and reliable evidence of improved child outcomes could likewise strengthen the case for adequate and sustained funding needed to track evolving and longer-term outcomes. Such data would be integral in to tracking systems involvement over time across states. Or likewise exploring how access or exposure to differing combinations of welfare services and programs influences developmental trajectories and outcomes including educational and health outcomes. More specifically, these data would allow us to better examine how social safety nets shape the consequences of early life disadvantage. For example, the association between early childhood poverty and human capital development or health may be weaker in states with strong social safety nets. Furthermore, the timing and packaging of social welfare policies may vary depending on the sociopolitical climate of a given state or country. In sum, it is incredibly important that we make continuous efforts to equip ourselves with robust data sources—as I do in my third dissertation chapter—that can enable us to answer these and other such important and understudied questions.

Appendix

Table A1. Effect of income on child care type with bootstrap standard errors.

	Full Sample RRR (SE)						One Dependent RRR (SE)						Two+ Dependents RRR (SE)					
	Parent vs.:		FCC vs.:		CBC vs.:		Parent vs.:		FCC vs.:		CBC vs.:		Parent vs.:		FCC vs.:		CBC vs.:	
	FCC	CBC	Parent	CBC	Parent	FCC	FCC	CBC	Parent	CBC	Parent	FCC	FCC	CBC	Parent	CBC	Parent	FCC
Age 1 Child Care Type																		
Income	1.04	1.13	0.96	1.09	0.89	0.92	1.35	87.27	0.74	64.65	0.01	0.02	0.97	1.05	1.03	1.09	0.95	0.92
	(0.19)	(0.18)	(0.17)	(0.20)	(0.14)	(0.17)	(15.41)	(2,740.30	(8.45)	(1,398.64	(0.36)	(0.33)	(0.12)	(0.16)	(0.13)	(0.18)	(0.14)	(0.15)
Constant	0.74	0.02+	1.35	0.02	59.25+	43.83	0.01	0.00	121.09	0.00	3.28e+30	2.71e+28	2.98	0.03	0.34	0.01	29.38	87.62
	(1.90)	(0.04)	(3.47)	(0.06)	(140.24)	(120.00	(1.42)	(0.00)	(20,874.26)	(0.00)	(1.64e+33)	(9.40e+30)	(7.27)	(0.11)	(0.82)	(0.04)	(91.72)	(297.70)
Observations	2,362	2,362	2,362	2,362	2,362	2,362	810	810	810	810	810	810	1,552	1,552	1,552	1,552	1,552	1,552
Age 3 Child Care Type																		
Income	0.98	1.26*	1.02	1.29+	0.79*	0.77+	0.06	1.59	15.42	24.45	0.63	0.04	1.02	1.29+	0.98	1.26+	0.78+	0.79+
	(0.11)	(0.14)	(0.12)	(0.19)	(0.09)	(0.11)	(2.32)	(52.49)	(459.97)	(1,271.78	(17.44)	(2.13)	(0.14)	(0.18)	(0.14)	(0.16)	(0.11)	(0.10)
Constant	0.87	0.02*	1.15	0.03+	45.62*	39.73+	6.33e+17	0.00	0.00	0.00	2,813.71	1.78e+21	0.17	0.00*	5.97	0.02	331.58*	55.54
	(1.52)	(0.04)	(2.01)	(0.06)	(83.17)	(86.89)	(3.63e+20)	(0.19)	(0.00)	(0.00)	(1,252,417.21	(1.49e+24)	(0.49)	(0.01)	(17.54)	(0.05)	(914.35)	(150.72)
Observations	2,328	2,328	2,328	2,328	2,328	2,328	670	670	670	670	670	670	1,658	1,658	1,658	1,658	1,658	1,658
Age 3 Child Care Type - Wave 3 EITC																		
Income	1.05	1.12**	0.95	1.06+	0.89**	0.94+	1.22	1.30	0.82	1.06	0.77	0.94	1.04	1.11**	0.96	1.06+	0.90**	0.94+
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.22)	(0.23)	(0.15)	(0.17)	(0.12)	(0.15)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)
Constant	1.09	1.71	0.92	1.57	0.59	0.64	2.04	3.29	0.49	1.61	0.30	0.62	0.44	1.03	2.26	2.32	0.97	0.43
	(0.84)	(1.47)	(0.72)	(1.17)	(0.50)	(0.47)	(5.08)	(7.67)	(1.21)	(3.72)	(0.68)	(1.43)	(0.38)	(0.91)	(1.94)	(2.20)	(0.86)	(0.41)
Observations	2,328	2,328	2,328	2,328	2,328	2,328	670	670	670	670	670	670	1,658	1,658	1,658	1,658	1,658	1,658

Notes: All controls included in each model. Standard errors in parentheses.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Table A2. Effect of income on child care sequences with bootstrap standard errors.

	Informal Only vs.:			Entry Formal vs.:			Exit Formal vs.:			Stable Formal vs.:		
	Entry Formal	Exit Formal	Stable Formal	Informal Only	Exit Formal	Stable Formal	Informal Only	Entry Formal	Stable Formal	Informal Only	Entry Formal	Exit Formal
Full Sample RRR (SE)												
Income	1.15	0.72	1.37+	0.87	0.63*	1.20	1.40	1.60*	1.92*	0.73+	0.83	0.52*
	(0.13)	(0.15)	(0.25)	(0.10)	(0.15)	(0.23)	(0.29)	(0.37)	(0.54)	(0.13)	(0.16)	(0.15)
Constant	0.04+	0.55	0.00**	24.36+	13.41	0.01+	1.82	0.07	0.00+	4,268.75**	175.22+	2,350.29+
	(0.07)	(1.78)	(0.00)	(40.44)	(48.74)	(0.02)	(5.87)	(0.27)	(0.00)	(12,081.32)	(505.80)	(10,410.87)
Observations	2,144	2,144	2,144	2,144	2,144	2,144	2,144	2,144	2,144	2,144	2,144	2,144
One Dependent in Household RRR (SE)												
	Informal Only vs.:			Entry Formal vs.:			Exit Formal vs.:			Stable Formal vs.:		
	Entry Formal	Exit Formal	Stable Formal	Informal Only	Exit Formal	Stable Formal	Informal Only	Entry Formal	Stable Formal	Informal Only	Entry Formal	Exit Formal
Income	9.22	100.19	21.62	0.11	10.87	2.35	0.01	0.09	0.22	0.05	0.43	4.63
	(112.59)	(2,418.22)	(209.71)	(1.33)	(180.16)	(15.48)	(0.25)	(1.56)	(4.05)	(0.45)	(2.83)	(85.14)
Constant	0.00	0.00	0.00	3.16e+15	0.00	0.00	7.44e+34	2.35e+19	8.07e+13	9.21e+20	291,498.57	0.00
	(0.00)	(0.00)	(0.00)	(4.98e+17)	(0.00)	(0.00)	(2.63e+37)	(6.78e+21)	(2.39e+16)	(1.30e+23)	(31803543.11	(0.00)
Observations	601	601	601	601	601	601	601	601	601	601	601	601
Two or More Dependents in Household RRR (SE)												
	Informal Only vs.:			Entry Formal vs.:			Exit Formal vs.:			Stable Formal vs.:		
	Entry Formal	Exit Formal	Stable Formal	Informal Only	Exit Formal	Stable Formal	Informal Only	Entry Formal	Stable Formal	Informal Only	Entry Formal	Exit Formal
Income	1.13	0.72	1.40+	0.88	0.64	1.24	1.38	1.56	1.94*	0.71+	0.81	0.52*
	(0.15)	(0.18)	(0.27)	(0.12)	(0.18)	(0.23)	(0.35)	(0.45)	(0.55)	(0.14)	(0.15)	(0.15)
Constant	0.03	8.98	0.00**	30.89	277.49	0.00*	0.11	0.00	0.00*	43,016.55**	1,392.41*	386,375.84
	(0.08)	(41.71)	(0.00)	(73.89)	(1,410.81)	(0.00)	(0.52)	(0.02)	(0.00)	(174,418.88)	(4,988.61)	(2,143,954.
Observations	1,543	1,543	1,543	1,543	1,543	1,543	1,543	1,543	1,543	1,543	1,543	1,543

Notes: All controls included in each model. Standard errors in parentheses.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Table A3. Effect of income on child care transitions with bootstrap standard errors.

	0 transitions vs.:			1 transition vs.:			2 transitions vs.:			3 transitions vs.:		
Full Sample RRR (SE)												
	1 transition	2 transitions	3 transitions	0 transitions	2 transitions	3 transitions	0 transitions	1 transition	3 transitions	0 transitions	1 transition	2 transitions
Income	1.32	0.96	1.12	0.76	0.72	0.85	1.04	1.38	1.17	0.89	1.18	0.85
	(29.33)	(17.73)	(8.07)	(16.78)	(29.46)	(24.88)	(19.32)	(56.08)	(13.45)	(6.38)	(34.38)	(9.76)
Constant	0.00	0.64	0.08	1,163.02	745.76	91.53	1.56	0.00	0.12	12.71	0.01	8.15
	(0.29)	(178.40)	(8.49)	(387,114.66	(455,295.19	(40,219.70)	(433.89)	(0.82)	(21.09)	(1,370.11)	(4.80)	(1,400.07)
Observations	1,626	1,626	1,626	1,626	1,626	1,626	1,626	1,626	1,626	1,626	1,626	1,626
One Dependent in Household RRR (SE)												
	0 transitions vs.:			1 transition vs.:			2 transitions vs.:			3 transitions vs.:		
	1 transition	2 transitions	3 transitions	0 transitions	2 transitions	3 transitions	0 transitions	1 transition	3 transitions	0 transitions	1 transition	2 transitions
Income	2.95	0.00	0.11	0.34	0.00	0.04	531.25	1,568.80	55.98	9.49	28.03	0.02
	(6.52)	(0.02)	(0.79)	(0.75)	(0.01)	(0.25)	(5,205.49)	(15,243.47)	(287.65)	(71.12)	(191.53)	(0.09)
Constant	0.00	1.18e+42	2.03e+15	698227566.12	8.25e+50	1.42e+24	0.00	0.00	0.00	0.00	0.00	5.82e+26
	(0.00)	(1.75e+44)	(2.29e+17)	(2.36e+10)	(1.22e+53)	(1.47e+26)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(4.59e+28)
Observations	573	573	573	573	573	573	573	573	573	573	573	573
Two or More Dependents in Household RRR (SE)												
	0 transitions vs.:			1 transition vs.:			2 transitions vs.:			3 transitions vs.:		
	1 transition	2 transitions	3 transitions	0 transitions	2 transitions	3 transitions	0 transitions	1 transition	3 transitions	0 transitions	1 transition	2 transitions
Income	1.32	1.05	1.24	0.76	0.80	0.94	0.95	1.25	1.18	0.80	1.06	0.85
	(0.74)	(0.34)	(0.92)	(0.43)	(0.48)	(0.56)	(0.30)	(0.76)	(0.90)	(0.60)	(0.62)	(0.65)
Constant	0.00	0.05	0.00	1,899.79	93.15	2.99	20.40	0.01	0.03	635.38	0.33	31.15
	(0.01)	(0.28)	(0.02)	(19,517.39)	(1,057.21)	(31.88)	(117.88)	(0.12)	(0.47)	(8,800.49)	(3.57)	(456.49)
Observations	1,053	1,053	1,053	1,053	1,053	1,053	1,053	1,053	1,053	1,053	1,053	1,053

Notes: All controls included in each model. Standard errors in parentheses.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

References

Adams, G., and Rohacek, M. (2010). *Child care instability: Definitions, context, and policy implications*. Washington, DC: Urban Institute.

Andersson, M. A. (2016). Health returns to education by family socioeconomic origins, 1980–2008: Testing the importance of gender, cohort, and age. *SSM-population health*, *2*, 549-560.

Ansari, A., & Winsler, A. (2013). Stability and sequence of center-based and family childcare: Links with low-income children's school readiness. *Children and Youth Services Review*, 35 (2): 358–66.

Arteaga, I., Humpage, S., Reynolds, A. J., & Temple, J. A. (2014). One year of preschool or two: Is it important for adult outcomes?. *Economics of Education Review*, 40, 221-237.

Athreya, K., Reilly, D., & Simpson, N. (2012). The Earned Income Tax Credit for single mothers: Insurance without disincentives? Colgate University Working Paper.

Barnett, W. S., Jung, K., Youn, M., & Frede, E. C. (2013). Abbott preschool program longitudinal effects study: Fifth grade follow-up. *New Brunswick, NJ: National Institute for Early Education Research*, *10*, 2001-2004.

Bastian, J., & Michelmore, K. (2018). The long-term impact of the earned income tax credit on children's education and employment outcomes. *Journal of Labor Economics*, *36*(4), 1127-1163.

Basu, A., Coe, N. B., & Chapman, C. G. (2018). 2SLS versus 2SRI: Appropriate methods for rare outcomes and/or rare exposures. *Health Economics*, 27(6), 937-955.

Becker, G. S. (1981). A treatise on the family. Cambridge, MA: Harvard University Press.

Becker, G. S., & Tomes, N. (1986). Human capital and the rise and fall of families. *Journal of Labor Economics*, 4, S1-S39.

Belsky J., and Pluess, M. (2009). Beyond diathesis stress: Differential susceptibility to environmental influences. *Psychological Bulletin*, 135, 885–908.

Berger, L. M., Font, S. A., Slack, K. S., & Waldfogel, J. (2017). Income and child maltreatment in unmarried families: evidence from the earned income tax credit. *Review of Economics of the Household*, 15(4), 1345-1372.

Bernal, R., & Keane, M. P. (2011). Child care choices and children's cognitive achievement: The case of single mothers. *Journal of Labor Economics*, 29(3), 459–512.

Bigras, N., Bouchard, C., Cantin, G., Brunson, L., Coutu, S., Lemay, L., ... & Charron, A. (2010, June). A comparative study of structural and process quality in center-based and family-based child care services. In *Child & Youth Care Forum* (Vol. 39, No. 3, pp. 129-150). Springer US.

Bivens, J., GarcĆa, E., Gould, E., Weiss, E., & Wilson, V. (2016). It's Time for an Ambitious National Investment in America's Children: Investments in Early Childhood Care and Education Would Have Enormous Benefits for Children, Families, Society, and the Economy. *Economic Policy Institute*.

Blair, C., & Raver, C.C. (2015). School readiness and self-regulation: a developmental psychobiological approach. *Annual Review of Psychology*, 66, 711-731.

Bratsch-Hines, M. E., Mokrova, I., Vernon-Feagans, L., & Family Life Project Key Investigators. (2017). Rural families' use of multiple child care arrangements from 6 to 58 months and children's kindergarten behavioral and academic outcomes. *Early Childhood Research Quarterly*, *41*, 161-173.

Bronfenbrenner, U. (1989). Ecological systems theory. *Annals of Child Development*, 6, 187–249.

Brooks–Gunn, J., Han, W. J., & Waldfogel, J. (2002). Maternal employment and child cognitive outcomes in the first three years of life: The NICHD study of early child care. *Child development*, 73(4), 1052-1072.

Capizzano, J., & Adams, G. (2003). Children in low-income families are less likely to be in center-based child care. *Development*, 71(4), 960-80.

Center on Budget and Policy Priorities. (2017). Policy Basics: State Earned Income Tax Credits. Retrieved from http://www.cbpp.org/research/state-budget-and -tax/policy-basics-state-earned-income-tax-credits.

Center on the Developing Child at Harvard University. (2010). *The Foundations of Lifelong Health Are Built in Early Childhood*. Retrieved from www.developingchild. harvard.edu.

Chapman, C., & Brooks, J. (2016). Treatment effect estimation using nonlinear two-stage instrumental variable estimators: Another cautionary note. *Health Services Research*, 51(6): 2375-2394.

Chaudry, A. (2004). *Putting Children First: How Low-Wage Working Mothers Manage Child Care*. New York: Russell Sage Foundation.

Chaudry, A., Morrissey, T., Weiland, C., & Yoshikawa, H. (2017). Cradle to kindergarten: A new plan to combat inequality. Russell Sage Foundation.

Chetty, R., Friedman, J. N., & Saez, E. (2013). Using differences in knowledge across neighborhoods to uncover the impacts of the EITC on earnings. *American Economic Review*, 103(7), 2683-2721.

Child Care and Development Fund, 45 C.F.R. § 98.20 (2019). https://www.govinfo.gov/app/details/CFR-2019-title45- vol1/CFR-2019-title45-vol1-part98/summary.

Coley, R. L., Li-Grining, C. P., & Chase-Lansdale, P. L. (2013). Low-income families' child-care experiences: Meeting the needs of children and families. In From Welfare to Childcare (pp. 171-192). Psychology Press.

Coley, R. L., Votruba-Drzal, E., Collins, M.A., & Cook, K. D. (2016). Comparing public, private, and informal preschool programs in a national sample of low-income children. *Early Childhood Research Quarterly*, *36*, 91-105.

Cooper, B. R., & Lanza, S. T. (2014). Who benefits most from Head Start? Using latent class moderation to examine differential treatment effects. *Child development,* 85(6), 2317-2338.

Corcoran, L., & Steinley, K. (2017). Early childhood program participation, results from the National Household Education Surveys Program of 2016. First Look. NCES 2017-101. National Center for Education Statistics.

Crosnoe, R., Pickett, K. C., Smith, C., & Cavanagh, S. (2014). Changes in young children's family structures and child care arrangements. Demography, 51: 459–483.

Crosnoe, R., Purtell, K. M., Davis-Kean, P., Ansari, A., & Benner, A. D. (2016). The selection of children from low-income families into preschool. Developmental Psychology, 52(4), 599.

Cunha, F., Heckman, J., Lochner, L., and Masterov, D. (2006). Interpreting the evidence on life cycle skill formation. *Handbook of the Economics of Education,* 26(1): 698-747.

Currie, J., & Almond, D. (2011). Human capital development before age five. In *Handbook of labor economics* (Vol. 4, pp. 1315-1486). Elsevier.

Currie J. & Thomas, D. (1995). Does Head Start Make a Difference? *American Economic Review*, 85(3), 341-364.

Dahl, G. B., & Lochner, L. (2012). The impact of family income on child achievement: Evidence from the earned income tax credit. *American Economic Review*, *102*(5), 1927-56.

Danziger, S. K., Ananat, E. O., & Browning, K. G. (2004). Childcare subsidies and the transition from welfare to work. *Family Relations*, 53, 219–228.

Derrick-Mills, T. M. (2009). Incentives at the Eligibility Threshold: An Examination of Child Care Financial Assistance Policies. *Policy Perspectives*, *16*(1), 3-34.

Dowsett, C. J., Huston, A. C., Imes, A. E., & Gennetian, L. (2008). Structural and process features in three types of child care for children from high and low income families. Early Childhood Research Quarterly, 23(1), 69-93.

Duncan, G. J., Dorset, C. J., Classes, A., Magnuson, K., Pagane, L. S., Feinstein, L.,...Jape, C. (2007). School readiness and later achievement. *Developmental Psychology*, 43(6), 1428-1445.

Duncan, G. J., & Magnuson, K. (2013). The long reach of early childhood poverty. In Economic stress, human capital, and families in Asia (pp. 57-70). Springer Dordrecht.

Duncan, G. J., Magnuson, K., & Votruba-Drzal, E. (2014). Boosting family income to promote child development. *The Future of Children*, *24*(1), 99-120.

Enchautegui, M., Johnson, M., & Gelatt, J. (2015). *Who minds the kids when mom works a nonstandard schedule?* Washington, DC: The Urban Institute.

Ensminger, M. E., & Slusarcick, A. L. (1992). Paths to high school graduation or dropout: A longitudinal study of first-grade cohort. *Sociology of Education*, 65(2), 95-113.

Farkas, G., & Beron, K. (2004). The detailed age trajectory of oral vocabulary knowledge: Differences by class and race. *Social Science Research*, 33(3), 464-497.

Feller, A., Grindal, T., Miratrix, L., & Page, L. C. (2016). Compared to what? Variation in the impacts of early childhood education by alternative care type. *The Annals of Applied Statistics*, *10*(3), 1245-1285.

Forry, N. D., Tout, K., Rothenberg, L., Sandstrom, H., & Vesely, C. (2013). Child Care Decision-Making Literature Review. Washington, DC: Office of Planning. *Research and Evaluation, Administration for Children and Families, US Department of Health and Human Services*, 2013-45.

Fraga, L., Dobbins, D., & McCready, M. (2015). Parents and the high cost of child care: 2015 Report. Child Care Aware of America.

Friedman-Krauss, A., Barnett, W. S., & Nores, M. (2016). How Much Can High-Quality Universal Pre-K Reduce Achievement Gaps?. *Washington: Center for American Progress*.

Gormley, W. T., & Gayer, T. (2005). Promoting school readiness in Oklahoma an evaluation of Tulsa's pre-k program. *Journal of Human resources*, *40*(3), 533-558.

Gould, E., & Cooke, T. (2015). High quality child care is out of reach for working families. *Economic Policy Institute Issue Brief*, *404*(4).

Hamad, R., & Rehkopf, D. H. (2016). Poverty and child development: A longitudinal study of the impact of the Earned Income Tax Credit. *American Journal of Epidemiology*, 183(9), 775-784.

Han, W. J. (2004). Nonstandard work schedules and child care choices: Evidence from the NICHD Study of Early Child Care. *Early Childhood Research Quarterly*, 19 (2004), pp. 231-256.

Hanson, J. L., Hair, N., Shen, D. G., Shi, F., Gilmore, J. H., Wolfe, B. L., & Pollak, S. D. (2013). Family poverty affects the rate of human infant brain growth. *PloS one*, *8*(12), e80954.

Harding, J. F., & Paulsell, D. (2018). Improving access to early care and education: An equity-focused policy research agenda. *Princeton, NJ: Mathematica*.

Heckman, J. J., & Masterov, D. V. (2007). The productivity argument for investing in young children. *Applied Economic Perspectives and Policy*, 29(3), 446-493.

Henly, J. R., Sandstrom, H., Claessens, A., Pilarz, A. R., Gelatt, J., Kim, J., & Healy, O. (2015). Determinants of subsidy stability and child care continuity. Urban Institute, Washington, DC.

Hoynes, H., Rothstein, J., & Ruffini, K. (2017). Making work pay better through an expanded Earned Income Tax Credit. Driving Growth through Women's Economic Participation, 57.

Huston, A. C. (2017). Effects of United States Income and Work Supports Policies on Children in Low-Income Families. The Wiley Handbook of Early Childhood Development Programs, Practices, and Policies, 424-446.

Jednoróg, K., Altarelli, I., Monzalvo, K., Fluss, J., Dubois, J., Billard, C., ... & Ramus, F. (2012). The influence of socioeconomic status on children's brain structure. *PloS one*, *7*(8), e42486.

Johnson, A. D. (2017). Child care and child development in the United States. In E. Votruba-Drzal & E. Dearing (Eds.), The Wiley handbook of early childhood development programs, practices, and policies. Hoboken, NJ: John Wiley & Sons.

Johnson, S. B., Riis, J. L., & Noble, K. G. (2016). State of the art review: Poverty and the developing brain. Pediatrics, 137(4), 2015–75.

Jones, L. E., & Michelmore, K. (2018). The impact of the Earned Income Tax Credit on household finances. *Journal of Policy Analysis and Management*, *37*(3), 521-545.

Kimmel, J. (2006). Child care, female employment, and economic growth. *Community Development*, 37(2), 71-85.

Knudsen, E.I., Heckman, J.J., Cameron, J.L., & Shonkoff, J.P. (2006). Economic, neurobiological, and behavioral perspectives on building America's future workforce. *Proceedings of the National Academy of Sciences*, 103(27), 10155-10162.

Kornrich, S., & Furstenberg, F. (2013). Investing in children: Changes in parental spending on children, 1972–2007. Demography, 50(1), 1-23.

Lareau, A. (2002). Invisible inequality: Social class and childrearing in black families and white families. *American sociological review*, 747-776.

Laughlin, L. (2013). Who's minding the kids– child care arrangements: Spring 2011 (No. P70-135). Washington, D.C: U.S. Census Bureau.

Loeb, S., Bridges, M., Bassock, D., Fuller, B., & Rumberger, R. (2007). How much is too much? The influence of preschool centers on children's social and cognitive development. *Economics of Education Review*, 26, 52–66.

Loeb, S., Fuller, B., Kagan, S. L., & Carrol, B. (2004). Child care in poor communities: Early learning effects of type, quality, and stability. *Child Development*, *75*(1), 47–65.

London, A.S., Scott, E.K., Edin, K., and Hunter, V. (2004). Welfare reform, work-family tradeoffs, and child well-being. *Family Relations*, 53 (2), pp. 148-158.

Magnuson, K., & Duncan, G. J. (2016). Can early childhood interventions decrease inequality of economic opportunity? RSF: *The Russell Sage Foundation Journal of the Social Sciences*, 2(2), 123-141.

Magnuson, K. A., Ruhm, C., & Waldfogel, J. (2007). Does prekindergarten improve school preparation and performance? *Economics of Education Review*, 26, 33-51.

Mamedova, S., & Redford, J. (2015). Early Childhood Program Participation, from the National Household Education Surveys Program of 2012. First Look. NCES 2013-029. Rev. National Center for Education Statistics.

Maynard, M., & Dollins, D. (2002). Participation in the Earned Income Tax Credit Program for Tax Year 1996 (Research Project 12.26). Internal Revenue Service, SB/SE Research.

Meyer, B. D. (2010). The effects of the EITC and recent reforms. Tax Policy and the Economy. Edited by J. Brown. Cambridge, MA: MIT Press. Vol. 24, pp. 153–80.

Meyers, M. K., & Jordan, L. P. (2006). Choice and accommodation in parental child care decisions. *Community Development*, 37(2), 53-70.

Meyers, M. K., Peck, L. R., Davis, E. E., Collins, A., Kreader, J. L., Georges, A., ... & Olson, J. A. (2002). The Dynamics of Child Care Subsidy Use: A Collaborative Study of Five States.

Morrissey, T. W. (2010). Sequence of Child Care Type and Child Development: What Role Does Peer Exposure Play? *Early Childhood Research Quarterly* 25 (1): 33–50.

National Academies of Sciences, Engineering, and Medicine [NASEM]. (2019). *A roadmap to reducing child poverty*. National Academies Press.

National Bureau of Economic Research (2017). TAXSIM, version 27. http://www.nber.org/taxsim/.

National Institute of Child Health and Human Development Early Child Care Research Network, & Duncan, G. J. (2003). Modeling the impacts of child care quality on children's preschool cognitive development. Child development, 74(5), 1454-1475.

National Institute of Child Health and Human Development Early Child Care Research Network. (2000). The relation of child care to cognitive and language development. Child Development, 960-980.

National Scientific Council on the Developing Child. (2012). *The Science of Neglect: The Persistent Absence of Responsive Care Disrupts the Developing Brain: Working Paper No. 12*. Retrieved from www.developingchild.harvard.edu.

National Scientific Council on the Developing Child (2020). *Connecting the Brain to the Rest of the Body: Early Childhood Development and Lifelong Health Are Deeply Intertwined Working Paper No. 15*. Retrieved from www.developingchild.harvard.edu.

Newey, W. K. (1987). Efficient estimation of limited dependent variable models with endogenous explanatory variables. *Journal of Econometrics*, 36(3), 231-250.

Nichols, A., & Rothstein, J. (2015). *The earned income tax credit (eitc)* (No. w21211). National Bureau of Economic Research.

Noble, K. G., Houston, S. M., Brito, N. H., Bartsch, H., Kan, E., Kuperman, J. M., ... & Schork, N. J. (2015). Family income, parental education and brain structure in children and adolescents. Nature neuroscience, 18(5), 773.

Pac, J., Nam, J., Waldfogel, J., & Wimer, C. (2017). Young child poverty in the United States: Analyzing trends in poverty and the role of anti-poverty programs using the Supplemental Poverty Measure. *Children and Youth Services Review,* 74(1), 35-49.

Pilarz, A. R. (2018). Multiple child care arrangements and school readiness in kindergarten. *Early Childhood Research Quarterly*, Volume 42, Pages 170-182.

Pilarz, A. R., Claessens, A., & Gelatt, J. (2016). Patterns of child care subsidy use and stability of subsidized care arrangements: Evidence from Illinois and New York. *Children and Youth Services Review*, 65, 231-243.

Pilarz, A. R., and Hill, H. D. (2014). Unstable and Multiple Child Care Arrangements and Young Children's Behavior. *Early Childhood Research Quarterly*, 29 (4): 471–83.

Reichman, N. E., Teitler, J. O., & McLanahan, S. S. (2001). Fragile Families: Sample and design. *Children and Youth Services Review*, 23(4/5), 303–326.

Rohaly, J. (2007). Reforming the child and dependent care tax credit. *Tax Policy Center Report. Tax Policy Center, Urban Institute and Brookings Institution, Washington, DC. Available at http://www. urban. org/publications/411474. html*.

Ross, C. E., & Mirowsky, J. (2006). Sex differences in the effect of education on depression: resource multiplication or resource substitution?. *Social science & medicine*, *63*(5), 1400-1413.

Sandstrom, H., and Huerta, S. (2013). The negative effects of instability on child development: A research synthesis. Washington, DC: Urban Institute.

Scott, E. K., & Abelson, M. J. (2016). Understanding the relationship between instability in child care and instability in employment for families with subsidized care. *Journal of Family Issues*, *37*(3), 344-368.

Scott, E., London, A., & Hurst, A. (2005). Instability in patchworks of child care when moving from welfare to work. *Journal of Marriage and Family*, 67, 370–386.

Semega, J., Kollar, M., Creamer, J., & Mohanty, A. (2019). Income and poverty in the United States: 2018. *Current Population Reports*, (P60-266).

Shanks, T. R., & Danziger, S. K. (2010). Anti-poverty policies and programs for children and families. *Social policy for children and families: A risk and resilience perspective*, 25-26.

Solon, G., Haider, S. J., & Wooldridge, J. M. (2015). What are we weighting for?. *Journal of Human Resources*, 50(2), 301-316.

Terza, J., Basu, A., & Rathouz, P. (2008). Two-stage residual inclusion estimation: Addressing endogeneity in health econometric modeling. *Journal of Health Economics*, 27(3), 531-543.

Tran, H., & Winsler, A. (2011). Teacher and center stability and school readiness among low-income, ethnically diverse children in subsidized, center-based child care. *Children and Youth Services Review*, 33(11), 2241-2252.

U.S. Census Bureau. (2017). Poverty Status of Related Children Under 6 Years of Age: 1969 to 2016.

von Hippel, P. T. (2007). Regression with missing Ys: An improved strategy for analyzing multiply imputed data. *Sociological Methodology*, 37(1), 83-117.

von Hippel, P. T., Workman, J., & Downey, D. B. (2018). Inequality in reading and math skills forms mainly before kindergarten: A replication, and partial correction, of “Are schools the great equalizer?”. *Sociology of Education*, 91(4), 323-357.

Votruba-Drzal, E., Levine Coley, R., & Lindsay Chase-Lansdale, P. (2004). Child care and low-income children's development: Direct and moderated effects. *Child development*, *75*(1), 296-312.

Weiland, C., & Yoshikawa, H. (2013). Impacts of a prekindergarten program on children's mathematics, language, literacy, executive function, and emotional skills. *Child Development,* 84, 2112-2130.

Yoshikawa, H., Weiland, C., & Brooks-Gunn, J. (2016). When does preschool matter?. The Future of Children, 26(2), 21-35.

Yoshikawa, H., Weiland, C., Brooks-Gunn, J., Burchinal, M. R., Espinosa, L. M., Gormley, W. T., ... Zaslow, M. J. (2013). *Investing in our future: The evidence base on preschool education*. Ann Arbor, MI: Society for Research in Child Development.