BUILDING A DATA INFRASTRUCTURE TO STUDY LOCAL AVAILABILITY IN CHILDCARE FOR CHILDREN OF IMMIGRANT AND U.S.-BORN PARENTS: A CONDITIONAL LOGIT MODEL ANALYSIS

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ABSTRACT

Qi Wang Xing: Building a Data Infrastructure to Study Local Availability in Childcare for Children of Immigrant and U.S.-Born Parents: A Conditional Logit Model Analysis
(Under the direction of Lora Cohen-Vogel)

In the United States, children of immigrants are more likely to start school at an academic disadvantage when compared to their peers with U.S.-born parents (Crosnoe, 2007; Han, 2008; Magnuson, Lahaie, & Waldfogel, 2006). It is possible that the disadvantage may be at least in part explained by differences in access to and use of high-quality childcare opportunities prior to the Kindergarten year. Indeed, while research has pointed to the benefits associated with high-quality early childhood education and public investments in expanding preschool enrollment, the children of immigrants continue to enroll in center-based care at lower rates compared to the children of U.S.-born parents (Brandon, 2004; Kahn & Greenberg, 2010; Karoly & Gonzalez, 2011; Takanishi, 2004). This study seeks to understand whether and how the supply of childcare services available in a neighborhood and other contextual factors contribute to differences in early education experiences by parental immigration status.

Building a first of its kind dataset, I combined data from the Early Childhood Longitudinal Study, the Common Core of Data, the Early Childhood Learning and Knowledge Center Head Start Data Project, the Homeland Infrastructure Foundation-Level Data, and the U.S. Census Bureau to examine whether and how childcare supply affects childcare use between immigrant and U.S.-born parents. Using a conditional logit model, I find that the supply of childcare centers, Head Start, and state pre-K programs differs between children of immigrant and U.S.-born parents, and the supply of childcare centers, in particular, had differential effects on center enrollment by parental immigration status. Having at least one immigrant parent negatively impacted the odds of center participation, and, even having more access to childcare centers could not offset its negative effect. Implications of these findings and recommendations to improve the overall data quality are discussed

To my husband, Chen, who has always challenged me to be better. You make my world wonderful. To my children, Chloe and Aspen, who inspired me to write this dissertation. You are everything. And, to my Grandfather, Lianwen, who had always believed in me and would have been proud.

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LIST OF ABBREVIATIONS

ACS	American Community Survey
CCD	Common Core of Data
CCDBG	Child Care and Development Block Grant
CCDF	Child Care Development Fund
CLM	Conditional logit model
ECLKC	Early Childhood Learning and Knowledge Center
ECLS-K:2011	Early Childhood Longitudinal Study Kindergarten Class 2011
FCC	Family childcare
GIS	Geographic Information Software
HAA	Heterogeneous availability in alternatives
HILFD	Homeland Infrastructure Foundational-Level Data
MNL	Multinomial logit model
SSBG	Social Services Block Grant
TANF	Temporary Assistance for Needy Families
ZBP	Zip Code Business Pattern

CHAPTER 1: INTRODUCTION

1.1 Background

Children of immigrants constitute the fastest growing population of children in the United States. The number of children from immigrant families has been growing at nearly four times the rate of that of children of U.S.-born parents, accounting for all population growth in children from birth to age 17 since 2000 (Fortuny & Chaudry, 2012). Among children age six and under, children of immigrants make up more than 25 percent of this population (Tienda & Haskins, 2011). This youngest group of children, who are also more racially and socioeconomically diverse than their peers of U.S.-born parents, is further increasing the cultural and linguistic diversity of America's schools (Sullivan, Houri, & Sadeh, 2016).

Researchers in the fields of sociology, developmental psychology, education, and economics have a burgeoning interest in the well-being and school readiness of younger children born to immigrant parents (e.g., Arzubiaga, Nogueron, & Sullivan, 2009a; Currie & Thomas, 1999; Fuligni & Yoshikawa, 2003; Portes & Rumbaut, 2001). This is likely due to the challenges these young children face as they enter the education system (Arzubiaga et al., 2009; Hernandez, 2004; Kao & Tienda, 1998; Portes & Rumbaut, 2001). Being a child of immigrant parents is associated with increased likelihood of experiencing various developmental risk factors, such as lack of English proficiency, lower levels of parental education, and family and neighborhood poverty and economic disadvantage (Capps, Fix, Ost, Reardon-Anderson, & Passel, 2004b; Fortuny, Hernandez, & Chaudry, 2010; Hernandez, 2004; Leventhal, Xue, & Brooks-Gunn, 2006; Pong & Hao, 2007).

Though researchers report great heterogeneity in the educational trajectories of children of immigrants across race/ethnicity, socioeconomic status, and parental country of origins (Kao & Tienda, 1995; Leventhal et al., 2006; Rong & Brown, 2001; Vernez, Abrahamse & Quigley, 1996), many agree that, on average, children of immigrants are more likely to start school at an academic disadvantage when compared to their peers of U.S.-born parents (Crosnoe, 2007; Han, 2008; Magnuson, Lahaie, & Waldfogel, 2006). Once in school, children of immigrants are also more likely to attend schools with high concentrations of poor and/or minority students, crowded classrooms, inadequate supplies of textbooks and materials, and poor school climate and safety (Crosnoe & Lopez-Gonzalez, 2005; Han, 2008; Waters, Mollenkopf, & Kasinitz, 2004; Roopnarine, Krishnakumar, Metindogan, & Evans, 2006).

To mitigate this early divide, researchers and policymakers are considering expanding access to high quality preschool programs. Research has pointed to the benefits associated with high-quality early childhood education and public investments in expanding preschool enrollment. Benefits accrue to children in form of better academic and socio-emotional outcomes, increased health, and improved educational attainment and employment outcomes (Belfield, Nores, Barnett, & Schweinhart, 2006; Campbell & Ramey, 1994; Reynolds & Temple, 1998). These benefits have led to increases in childcare subsidies and the expansion of government-funded early childhood education programs, and, subsequently, have dramatically increased center-based preschool participation rates in the United States (Barnett et al., 2016; Magnuson, Meyers, Ruhm, & Waldfogel, 2005; U.S. Department of Health and Human Services, 2016).

If participating in early education, such as a center-based preschool, has positive effects on achievement and economic outcomes later in life, then perhaps early childhood education, which may be the first education setting immigrant families encounter before entering the K-12 system, may also be a powerful policy lever to buffer against the set of developmental risk factors associated with growing up in immigrant families in the U.S. It has been well documented, however, that children of immigrants have lower rates of non-parental care use of any type, including center-based care, than do children of U.S.-born parents (Brandon, 2004; Kahn & Greenberg, 2010; Karoly & Gonzalez, 2011; Takanishi, 2004). On the other hand, little is known about (1) whether they have equitable access to preschool compared to peers of U.S.-born parents, and (2) how their childcare choices differ. Therefore, this study sought to understand whether and how community-level supply of childcare services contributes to differences in early education experiences by parental immigration status.

1.2 Statement of Purpose

In this study, I adapted two theoretical frameworks—heterogeneous availability of alternatives and spatial assimilation—to guide the study's problem conceptualization and variable selection. In doing so, I addressed the shortcomings in the current, if small, immigrant childcare choice literature. I combined data from the Early Childhood Longitudinal Study Kindergarten Class 2011, the Common Core of Data, the Early Childhood Learning and Knowledge Center Head Start data, the Homeland Infrastructure Foundation-Level Data, and the U.S. Census Bureau. Using a conditional logit model, I examined whether and how childcare supply affects the childcare use between immigrant and U.S.-born parents. Specifically, this dissertation answered two questions:

1. How does the supply of childcare options available for children of immigrants in the United States compare with the supply for children of U.S.-born parents?

2. How does the use of childcare vary between immigrant and U.S.-born parents? And, how does the concentration of immigrants living within a community mediate that use?

Findings from the conditional logit model analyses reveal that children of immigrant parents had more access to centers, Head Start, and state pre-K programs although they were enrolled in centers at lower rates than peers with U.S.-born parents. The number of childcare care centers did not significantly affect the likelihood of enrolling in center care, while having at least one immigrant parent negatively impacted the odds of center participation. In addition, the supply of childcare options, especially that of childcare centers, had differential effects on center enrollment by parental immigration status, and, even having more access to childcare centers did not offset the negative effect associated with having an immigrant parent, as measured by the predicted probabilities.

1.3 Significance

The study adds to our knowledge about childcare choices by conceptualizing those choices as a result of supply (or lack thereof), parental immigrant status, and other family-level attributes. Two frameworks—heterogeneous availability of alternatives from labor economics and spatial assimilation from sociology—contribute to a more realistic and appropriate framework for studying this complex issue. In addition, I also combined multiple nationally representative data sets to create a comprehensive data set linking the family to the supply of each childcare alternative, using Geographical Information Software (GIS), to prove the appropriateness of new standards regarding the geographic perimeter around a family's zip code centroid. A Technical Report was developed and included as Appendix A to describe the attributes of each data set along with procedures to link them. These research and methodological contributions, as well as policy contribution are discussed in detail in the following sections.

1.3.1 Research contributions

The study is the first to empirically test whether and how the community-level supply of childcare alternatives affects family-level childcare choices for four-year-olds in the U.S. by parental immigration status, which addresses a persistent gap in the childcare choice literature. Previous research suggests that children of immigrants have lower participation rates in preschool than peers of U.S.-born parents, which, however, is based on the insufficient assumption that parents are free to choose any care arrangement they prefer. In any real choice situation, the choice alternatives and their attributes, combined with the decision-maker's attributes and preferences, always limit the actual choice set available to the decision-maker. The heterogeneous availability of alternatives framework provides a more appropriate lens for framing the choice situations as complex as they are.

Another research contribution of this study is the application of a new lens—the spatial assimilation of immigrant parents—in examining the intersection between immigration status and childcare choices. Previous research has extensively applied a developmental psychological approach by adding parental immigration status simply as a covariate in the model. This approach is insufficient because it overlooks the multifaceted nature of immigration status in the childcare choice context. The spatial assimilation framework instead highlights the role immigrants' residential locations play in childcare choices, and provides a set of indicators to explain variation in perceived opportunities and constraints for children of immigrants. It allowed me to explore how immigrant concentration affect childcare choices between children of immigrant and U.S.-born parents.

1.3.2 Methodological contributions

Earlier studies have detailed the disparities in preschool enrollment rates associated with parental immigration status, and separately, the distributional inequalities of childcare providers across neighborhoods (Fuller, Raudenbush, Wei, & Holloway, 1993; Vandell & Wolfe, 2000). Much less is known about how the community-level availability/supply of childcare services affects family-level choices. This reveals data and methodological limitations in linking community-level supply data and family-level choice data together (Blau, 1993; Fuller et al., 2004).

The first methodological contribution of this study pertains to data comprehensiveness. I combined several nationally representative data sets, including two survey data sets and four administrative data sets, to create a comprehensive data set that represents both the supply of *each* childcare alternative and the characteristics of a child's family and residential location. Some of these data sets, such as the Homeland Infrastructure Foundational-Level Data and the Early Childhood Learning and Knowledge Center Head Start data, have not been used in any study before.

The second methodological contribution of this study is the use of the Geographical Information Software which has not often been used in education research. The challenge of linking multiple data sets to the main research data set, the ECLS-K:2011, is that data from other sources are collected by different federal agencies at different geographic levels. GIS proves to be a useful tool in this situation, as it can add layers of data at different geographical levels to a single geographic point. In my study, the geographic point is each family's zip code centroid. A zip code centroid is the physical center of a zip code polygon. This widens the opportunity in linking other contextual data to address educational questions that are often situated in complex societal, political, and economic context.

The third methodological contribution is the use of a discrete choice model, the *conditional logit model*. Unlike previous empirical models used in childcare choice studies, such as OLS, binary models, or multinomial logit models, that focus only on child or family attributes, the conditional logit model takes into consideration supply-specific characteristics (e.g., quantity), *in addition to* child- and family-specific characteristics. This model not only aligns with the study's conceptual framework, but is also more realistic in choice situations where supply and demand interact to affect choice outcomes.

1.3.3 Policy contribution

The disparities in enrollment in early education programs between children of immigrant parents and children of U.S.-born parents are concerning because they are consistent with a school readiness gap by parental immigration status (Crosnoe, 2007; Magnuson, Lahaie & Waldfogel, 2006). Because school readiness predicts later academic achievement (Duncan et al., 2007; Magnuson & Waldfogel, 2016), creating public policies that promote equitable access to high-quality early childhood education has potential for narrowing gaps by preparing children academically and socio-emotionally for school. Therefore, it is imperative to first understand the supply of childcare in communities where immigrant families reside. With a better understanding, policies may be designed to expand access to early childhood education for children of immigrants, especially those living in poverty with limited access to preschool.

In the chapters that follow, I first reviewed the literature on childcare choices in general and discuss particular barriers in access to childcare among children of immigrants in Chapter 2. In Chapter 3, I used the heterogeneous availability of alternatives and spatial assimilation frameworks to guide the conceptualization of this study. In Chapter 4, I described the data sets and measures. I presented the findings from the conditional logit model analyses in Chapter 5. I ended this dissertation with some discussion in Chapter 6.

CHAPTER 2: LITERATURE REVIEW

The childcare market in the U.S. is “comprised of organizations and individuals that offer early care and education services” on one hand, and families with varying resources and needs for childcare on the other (Fuller et al., 2004, p.506). As will be shown, a review of the childcare choice literature suggests that our current understanding is heavily drawn from analyses focusing on family and child attributes as predictive influences. While this is important information in explaining the gap in preschool enrollment rates between children of immigrant and U.S.-born parents, little is known about how the childcare *supply* conditions childcare choice decisions made by immigrant and U.S.-born parents alike.

In this chapter, I began by describing the array of policies that govern early childhood care and education in the U.S., including both public and private childcare alternatives, and the distribution of these services (section 2.1). I then summarized common family and child attributes that are believed to be associated with childcare choices (section 2.2). Next, I presented studies examining childcare choice patterns by parental immigration status, and discussed common barriers to access facing children of immigrants (Section 2.3). I ended the literature review with justifications for the current study (Section 2.4).

2.1 Understanding Childcare Choices in the U.S.

In order to better understand the supply of childcare in the U.S., this section described the providers of childcare services under different early childhood care and education policies, and their distribution. Overall, providers can be categorized into six mutually exclusive childcare alternatives: Head Start, state pre-K, childcare centers, licensed family childcare homes, individual care providers, and parental care. These childcare alternatives not only differ in history, governance, and eligibility requirements (section 2.1.1), but are also disproportionately distributed across communities, creating different choice sets for individual families (section 2.1.2).

2.1.1 Early childhood polices in the U.S.

Prior to the 1960s, government involvement in pre-kindergarten education for four-year-olds in the U.S. was minimal, as the care of young children before school entry was widely considered a family responsibility (Rose, 2010). Today, a wide array of federal and state policies has been initiated to provide either free or subsidized preschool education, primarily targeted at children from economically disadvantaged backgrounds. The expansion of public funding to support low-income children's participation in center-based programs, especially Head Start and state pre-K, has led to an increased proportion of low-income families' participation in formal childcare during the 1990s (Magnuson, Meyers, & Waldfogel, 2007).

2.1.1.1 Head Start

As part of President Lyndon Johnson's War on Poverty campaign, Project Head Start was launched in 1965 to provide care and education for economically disadvantaged four-year-olds. It is administered by the Administration for Children and Families within the Department of Health and Human Services and allocates funds directly to each local grantee, bypassing the states. The program provides comprehensive child welfare services to eligible preschool-aged children living in poverty, including preschool education, health and nutrition services, and parent education (Swadener, 1995). Eligibility guidelines for Head Start require that family income not exceed 130% of the federal poverty level, though income requirements are relaxed for children with special needs (Kalifeh, Cohen-Vogel, & Grass, 2011). Since its inception, the program has served eligible children in all 50 states, the District of Columbia, and the outlying area of the U.S. Today, Head Start enrolls about 10% of the nation's four-year-olds and remains the sole federal program for preschool education (Barnett et al., 2016). With an enrollment over 925,000 preschool children, Head Start has more than doubled its enrollment since the 1980s (Office of Head Start, 2014).

2.1.1.2 State pre-kindergarten

Over the past 50 years[1], the notion of state pre-K has evolved from the rather ambiguous term "public preschool" piloted in a handful states to a well-defined educational program linked to the K–12 educational system in 42 states plus the District of Columbia (Bushouse, 2009; Rose, 2010). Now the largest public preschool provider, state pre-K programs enroll 28% of all four-year-olds in the U.S. (Barnett et al., 2016). State pre-K is a classroom-based preschool education program funded and administered by the state with the goal of educating four-year-olds, most of whom are "typically-developing" and living in poverty (Barnett, Friedman, Hustedt & Stevenson-Boyd, 2009; Gilliam & Zigler, 2000; Magnuson et al., 2004). Income requirements for program eligibility, targeted state pre-K as most state programmed are called, vary dramatically across states, ranging from below 100% to below 300% of the federal poverty level (Barnett et al., 2016). State pre-K enrollment has experienced even more dramatic expansion than Head Start, especially during the past decade and half, doubling from 14% of four-year-olds in 2002 to 28% in 2015 (Barnett et al., 2016).

[1] California, New York, and the District of Columbia were among the first to initiate state-funded pre-kindergarten programs to low-income children around the time Head Start was launched in the mid-1960s (Barnett et al., 2015; Fuller, 2007).

2.1.1.3 Childcare subsidies

Childcare subsides help eligible families with children under age 13 pay for childcare so that parents can seek/maintain work or participate in training or education activities (Blau, 2000; Blau & Tekin, 2003; Mckernan, Lerman, Pindus, & Valente, 2001). When it comes to preschool-aged childcare, childcare subsidies can allow parents to choose care arrangements that they could otherwise not afford. Parents typically receive vouchers that they can use to reimburse private providers directly (Smolensky & Gootman, 2003). Childcare subsidies have three major federal funding streams: the Childcare and Development Fund (CCDF), the Temporary Assistance for Needy Families (TANF), and the Social Services Block Grant (SSBG). In FY 2014, approximately 1.41 million children and over 850,000 families per month received childcare assistance. Among them, 67% were children under age 6, and 72% were cared for in a childcare center (Office of Head Start, 2015).

2.1.1.4 Special education and early childhood education

The *Individuals with Disabilities Education Act Amendment of 1986 (PL 99-457)* extended the free and appropriate public education guarantee to preschool children with special needs (Bushouse, 2009). This federal mandate also expanded the criteria of public preschool eligibility to include not only economic disadvantage but also disability—two statuses that have become the universal eligibility criteria across targeted state-funded pre-K programs (Gilliam & Zigler, 2000). Nationwide, three percent of all four-year-olds are enrolled in preschool programs through this provision (Snyder & Dillow, 2016).

2.1.1.5 Private childcare provision

Besides the two public preschool programs, Head Start and state pre-K, and various public grants that either offset the financial burdens associated with childcare for low-income families or ensure free preschool education for children with special needs, parents can also look to the private sector for childcare which is often fee-based. Private providers generally include organizations, such as childcare/daycare centers or preschool (center), and individuals, such as licensed family childcare (FCC) home providers, or relatives, babysitters/neighbors/friends to whom parents pay a relatively smaller amount of money compared to what they would pay for center care. The only type of childcare provided in the private sector that is free is parental care where the child is cared for by a parent.

Associated with the cost difference is the stringency of state regulations each type of childcare providers is required to follow. Childcare center, for example, are required to comply with state regulations on health and safety, child-staff ratios, staff qualifications and training, curriculum, and developmentally appropriate activities. Recently, the federal government has added rules for childcare providers serving children who receive the Child Care and Development Fund financial assistance. In 2014, the CCDBG Act was signed into law. The law identifies minimum health and safety requirements, training requirements, and monitoring requirements to ensure that childcare used by children receiving the CCDF financial assistance protects their health and safety. This applies to licensed family childcare home providers, who generally comply with some relaxed regulations. Other than these, individual providers are often unregulated care providers, and parents use them at their own discretion.

Together, childcare providers in the public and private sectors make up a complex childcare market, as summarized in Table 2. 1. *Formal care* used herein refers to care provided in a classroom-based setting, such as childcare centers, preschool, Head Start, or state-funded pre-K programs. Among them, formal care—preschool—is often considered to be of better quality and educational experience in preparing children ready for kindergarten, provided by caregivers who have a formal degree and specific training in child development. *Informal care* used herein refers to care provided in a home setting, either at the child's or caregiver's home, by an individual, such as a nanny/babysitter, a relative, a friend or a neighbor, or by a licensed individual at a family childcare (FCC) provider.

Table 2. 1 Summary of childcare policies in the U.S.

Childcare Alternative	**Formal vs. Informal**	**Sector**	**Governance Agency**
Head Start	Formal	Public	Federal
State pre-K	Formal	Public	State
Childcare center	Formal	Private (*may receive childcare subsidies*)	State (*federal compliance required if childcare subsidies are received*)
Licensed family childcare home	Informal	Private (*may receive childcare subsidies*)	State (*federal compliance required if childcare subsidies are received*)
Individuals (relative or non-relative)	Informal	Private (*may receive childcare subsidies*)	Not regulated (*federal compliance required if childcare subsidies are received*)
Parent	Informal	Private	Not regulated

2.1.2 Distribution of childcare supply in the U.S.

As shown above, six formal (center, Head Start, state pre-K) and informal (licensed FCC homes, individual providers, parent) childcare alternatives, together, constitute the provision of childcare services in the U.S. As with differences in costs and compliance requirements, these childcare alternatives vary greatly by setting (home vs. center), schedule (half-day, full-day, extended hours), cost, and quality (Blau, 2001), leading to stark distributional inequalities of childcare provision between less and more affluent areas (Fuller, Kagan, Caspary, & Gauthier, 2002; Fuller, Loeb, Strath, & Carrol, 2004; Gordon & Chase-Lansdale, 2001; Kreader, Brickman, Collins, Piecyk, & Collins, 1996; Queralt & Witte, 1998).

Among the few studies that focus on the supply side of childcare services, researchers have linked the childcare provision to community characteristics at census tract level (Herbst &

Barnow, 2008; Queralt & Witte, 1998), zip code level (Fuller & Liang, 1996; Fuller, Loeb, Strath & Carrol, 2004; Gordon & Chase-Lansdale, 2001; Hatfield, Lower, Cassidy, & Faldowski, 2015), and county level (Ficano, 2006; Fuller & Liang, 1996). These studies have found a clear association between childcare supply and three characteristics of the local community—level of poverty; employment patterns of the community's population, in particular, female labor force participation; and residential stability (Queralt & Witte, 1998).

The provision of formal childcare in poor communities is especially problematic at the zip code and census tract levels (Fuller, Coonerty, Kipnis, & Choong, 1997). For example, in examining the relationship between community socioeconomic characteristics and the local supply of childcare, studies show that significantly fewer childcare centers and fewer center slots were available in low-income communities (Burstein & Layzer, 2007; Collins, Layzer, & Kreader, 2007; Lee et al., 2004), although there was a better supply of family childcare homes in these poor communities (Gordon & Chase-Lansdale, 2001; Queralt & Witte, 1998). On the other hand, communities with higher female labor supply, greater numbers of highly educated females, and more children ages five and under, have a greater number of accessible childcare slots (center and family childcare homes) (Brandon, 2000; Coley, Votruba-Drzal, Collins, & Miller, 2014a; Dupere, Leventhal, Crosnoe, & Dion, 2010; Gordon & Chase-Lansdale, 2001; Herbst & Barnow, 2008; Queralt & Witte, 1998).

Research on the locational preferences of childcare centers may help explain the lack of center supply in economic disadvantaged communities. Kahn and Kamerman's interviews with childcare center directors (1987) identified several community features of preference. These include communities that are close to a major highway, are located between a middle-class residential area and commercial area, have high female labor force participation rates, and have married families with dual incomes more than 50% above the median income.

Studies examining the distribution of childcare supply at the county level reveal similar inequalities in childcare availability associated with county urbanization level and demographic features (Ficano, 2006; Fuller & Liang, 1996). Despite the expansion of the childcare industry at the county level as measured by the number of childcare workers, the increase has not been evenly distributed across counties. For example, less urbanized or rural counties experienced more viable changes in childcare quantity per child than their urban or urbanized counterparts (Ficano, 2006). Moreover, counties with growing proportions of Hispanic residents exhibit decreased expansion in the quantity of formal care arrangements (Ficano, 2006). This finding is consistent with other studies that note a preference toward kin care among Hispanics (e.g., (Brown-Lyons, Robertson, & Layzer, 2001).

2.2 Predicting Childcare Choices

Despite these handful studies that inform us about the supply of childcare and its distribution patterns, our current understanding of childcare choices is disproportionately shaped by an extensive literature focusing on family-level attributes (e.g., Fuller et al., 2004). Among them, economists consider the use of any non-parental care (individual providers, FCC home, or center-based care) a component of parents' decision to work outside the family and consumption choices. They assume that these choices reflect parents' preferences for certain type of childcare and budget constraints. That is, the more the childcare costs, the less likely the parent, mostly the mother, would join the labor force, but to stay at home caring for the child (Blau, 2001). Other social scientists, using human and social capital lenses, consider families' childcare choices as dependent on family income, parental educational attainment and employment, and family structure (e.g., Greenberg, 2011).

This literature, most of which relying on national samples and focusing on low-income families (Coley, Chase-Lansdale, & Li-Grining, 2001; Fuller, Kagan, Caspary, & Gauthier, 2002; Loeb, Fuller, Kagan, & Carrol, 2004; Zaslow, Oldham, Moore, & Magenheim, 1998), has conceptualized family and child attributes into two domains. As discussed below in detail, the first domain consists of each family's unique *resources and needs* (Buriel, Raymond ; Hurtado-Ortiz, 2000; Crosnoe, Purtell, Davis-Kean, Ansari, & Benner, 2016; Huston, Chang & Gennetian, 2002; Peyton, Jacobs, O'Brien, & Roy, 2001). These refer to a set of observable and unobservable attributes of the parents, family, and the child, such as family income, parental employment status (especially the mother's), parental educational attainment, marital status, number of children, the child's developmental stage (section 2.2.1). The second domain includes family *preferences* for certain type of care and *perceptions* of available childcare options within their communities (Chaudry et al., 2011; Fuller et al., 2004). These reflect parental priorities for desirable characteristics of childcare options based on values, beliefs, and assessments of available care options within the community, and are often unobservable (section 2.2.2). Mismatch between the two domains is discussed (section 2.2.3).

2.2.1 Resources and needs

Resources and needs refer to the financial and human capital as well as employment-related and child-related demands. Table 2. 2 summarizes these family- and child-level attributes. Most of the *resource* measures are often observables, such as family income, parental education, marital status, number of children, and race and ethnicity. The *need* measures, however, can be either observable or unobservable. For example, while the child's needs, in terms of temperament and developmental level, can help predict what type of childcare parents are likely to choose, the employment-related demands, such as employment related location and schedule, are often unobservable in the childcare literature. These attributes are discussed in the order of its prevalence in the literature in this section.

2.2.1.1 Family income

Childcare choices remain highly stratified by family income. It has been well documented that higher-income families are more likely than lower-income families to use center-based care (Blau, 2001; Bridges, Fuller, Rumberger, & Tran, 2004; Capizzano, Adams, & Sonenstein, 2000; Connelly & Kimmel, 2003; Duncan, Morris, & Rodrigues, 2011; Hirshberg, Huang, & Fuller, 2005; Kimmel, 2006; NICHD, 1998). For example, families from the top income quintile are nearly 1.5 times more likely to use center care than families from the lowest two income quintiles (Magnuson & Waldfogel, 2016). Despite the overall increases in preschool enrollment for all four-year-olds since the late 1960s (Magnuson, Meyers, & Waldfogel, 2007), longitudinal analyses from the Current Population Survey reveal that the income-related gap in preschool enrollment has been persistent, ranging from 15% to 30%, between less- and more-affluent families over time (Bainbridge, Meyers, Tanaka, & Waldfogel, 2005; Magnuson & Waldfogel, 2016).

This preschool enrollment gap by family income can be explained by the costs associated with center care, which is often too high for families with limited financial resources to afford. A 2016 report compares the average annual cost of full-time center care for a four-year-old to other household expenditures and earnings by state. The report reveals that childcare costs exceed or are comparable to (less than $500 difference) public college tuition and fees in 22 states, and cost more than one third of family income for a single-parent household in 31 states (Child Care

Aware of America, 2016). It is speculated that childcare can become a financial burden too heavy to be offset even with incomes for some families (Herbst & Barnow, 2008; Kimmel, 1998), therefore, excluding families with limited financial resources from choosing this option.

2.2.1.2 Parental employment status

Another factor that has been shown to predict childcare choices is parental employment status, especially that of the mother's. As the child's primary caregiver, the mother's employment status has the most direct impact on whether the family enters the childcare market to look for care outside the family. The relationship between maternal employment status and childcare choices, however, is often viewed as bidirectional. It follows that, while the mother's wage can affect which care option(s) are most affordable for the family, she needs to secure childcare first before she can join the workforce (Blau, 2003). Using the labor supply model and consumer choice theory to analyze maternal employment and childcare choices, economists speculate that the childcare choice reflects a mother's considerations over the childcare costs of different types, household wages, and budget constraints (Baum, 2002; Blau & Hagy, 1998; Connelly, 1992; Han & Waldfogel, 2001; Leibowitz, Linda, & Witsberger, 1988; Ribar, 1995). Higher childcare cost increases the likelihood that mothers with young children will not work (Anderson & Levine, 1999); Baum 2002; Kimmel, 1998; Jean Kimmel & Powell, 2006; McCall, Tittnich, & Snyder, 1994).

On the other hand, Census data from 2011 show that more than 7 out of 10 children under age 4 with employed mothers are in some form of non-parental care (Child Trends, 2016). Variations in childcare choices made by families with working mothers are often related to the mother's profession, race, marital status, and geographic location. Mothers who have professional jobs, who are African Americans, who work full-time, who are married, and who

Table 2. 2 List of studies examining effects of resources and needs

Attribute	Effects	Studies
Family income	Family income is positively associated with center participation	Bainbridge, Meyers, Tanaka & Waldfogel, 2005; Blau 2001; Bridges, Fuller, Rumberger & Tran, 2004; Capizzano et al., 2000; Connelly & Kimbel, 2003; Duncan, Morris & Rodrigues, 2011; Hirshberg, Huang & Fuller, 2005; Kimmel 2006; NICHD, 1998; Magnuson & Waldfogel, 2016
Parental employment	Bi-directional: Mother's employment status and wage are related to the use and type of non-parental care; Mother needs to secure non-parental care first which allows her to join the workforce	Anderson & Levin, 1999; Baum, 2002; Blau, 2001; Blau & Hagy, 1998; Brandon, 2004; Casper, 1997; Connelly, 1992; Connelly & Kimmel, 2003; Han & Waldfogel, 2000; Han & Waldfogel, 2001; Kimmel, 1998; Kimmel & Powell, 2006; Leibowitz, Waite & Witsberger, 1988; McCall, Tittnich & Snyder, 1994; Ribar, 1995
Parental education	Mother's education is positively associated with center enrollment	Bridges et al., 2004; Child Trends; 2016; Duncan, Morris & Rodrigues, 2011; Hirshberg, Huang & Fuller, 2005; Kim & Fram, 2009; Leibowitz et al., 1998; Wolfe & Scrivner, 2004
Marital status	Married couples have more resources to accommodate employment and childcare needs, and with the spouse comes another set of family members or relatives who may be able to provide additional social support to care for the child	Connelly & Kimmel, 2003; Edgell & Moen, 1999
Number of children	Number of children is negatively associated with center use	Bridges et al., 2004; Burstein & Layzer 2007; Chaudry, 2004; Chaudry et al., 2011; Hirshberg, Huang & Fuller, 2005; Singer, Fuller, Keiley & Wolf, 1998
Race and ethnicity	Inconsistent findings: racial/ethnic differences may reflect mean differences in family socio-demographic characteristics; families vary in the degree to which they maintain their own culture or embrace the wider societal norms	Barbarin et al., 2006; Brown-Lyons et al., 2001; Capizzano, Adams & Ost, 2006; Collins & Ribeiro, 2004; Delgado,2009; Early & Burchinal, 2001; Fuller et al., 1996; Fuller et al., 2002; Grogan, 2012; Huston et al., 2002; Liang et al., 2000; Magnuson & Waldfogel, 2016; Shlay, 2010; Singer, Fuller, Keiley & Wolf, 2000; Tang, Coley & Votruba-Drzal, 2012
Child attributes	The traits and behaviors of young children draw responses from parents who are sensitive to their child's age, level of development, and temperament when making childcare decisions	Casper, 1996; Clarke-Stewart & Allhusen, 2005; Coley, Votruba-Drzal, Collins & Millter, 2014; Crosby, Genetian & Huston, 2005; Crosnoe et al., 2016; Dowsett & Huston, 2005; Fuller et al., 2002; Gamble, Ewing & Wilhlem, 2009; Greenberg, 2011; Lowe & Weisner, 2004; Pianta & Walsh, 1996; Sandstrom & Chaudry, 2012; Scott, Edin, London & Mazelis, 2001; Tucker-Drob & Harden, 2012

live in central cities, have higher likelihood of choosing center-based care, and vice versa (Blau, 2001; Brandon, 2004; Casper, 1997; Connelly & Kimmel, 2003).

2.2.1.3 Parental educational attainment

In addition to family income and maternal employment, parental educational attainment, particularly the mother's level of education, is positively associated with choosing center-based care (Bridges et al., 2004; Duncan, Morris & Rodrigues, 2011; Hirshberg, Huang & Fuller, 2005; Kim & Fram, 2009; Leibowitz et al., 1998; Wolfe & Scrivner, 2004). Among children ages three to six, 79% of those whose mother has a bachelor's degree were enrollment in preschool, while the ratio was only 43% among children whose mother did not graduate from high school (Child Trends, 2016).

This preschool enrollment gap by maternal educational attainment can be explained in part by the economic returns to the mother's investments in education, which in turn contributes to family income. In general, women experience the highest returns in wage to secondary education than any other educational levels (Psacharopoulos & Patrinos, 2004). Among low-income mothers, in particular, the role of education has been significant in their struggles towards economic self-sufficiency (Blau & Beller, 1992; Hersch, 1991; Kimmel, 1998; Moffitt & Roff, 2000). Low-income mothers with a high school degree are found to be more likely to be employed and maintain employment than those who didn't graduate from high school (Urban & Olson, 2005). As a result, one may speculate that with more education, mothers with higher income may have more purchasing power over childcare than peers with less education (Bassok, French, Fuller, & Lynn Kagan, 2008).

2.2.1.4 Family structure: marital status and number of children

Some researchers are also interested in knowing how family structure or household composition, such as marital status and number of children, predict the type of childcare used. They believe that it reflects how a family allocates existing resources to meet varying needs (Connelly & Kimmel, 2003; Becker & Moen, 1999). Compared to single parents, married couples have more resources to accommodate employment and childcare needs, and with the spouse comes another set of family members or relatives who may be able to provide additional social support to care for the child. The number of children in a family has a negative association with choosing center care. Compared to families with fewer children, families with more children tend to choose informal care arrangements, such as parental, relative, family childcare homes, neighbors, and friends (Bridges et al., 2004; Burstein & Layzer, 2007; Chaudry, 2004; Chaudry et al., 2011; Hirshberg et al., 2005; Singer, Fuller, Keiley, & Wolf, 1998). Again, this may be related to the cost associated with center care for all children if these children are close in age.

2.2.1.5 Race and ethnicity

Race and ethnicity, which have been extensively studied in their relation to childcare choices, yield inconsistent findings (Capizzano, Adams, & Ost, 2006; Early & Burchinal, 2001; Fuller, Kagan, Caspary, & Gauthier, 2002; Huston, Chang, & Gennetian, 2002; Shlay, 2010; Singer et al., 1998; Tang, Coley, & Votruba-Drzal, 2012; Fuller et al., 2002; Huston et al., 2002; Shlay, 2010; Singer, Fuller, Keiley & Wolf, 2000; Tang, Coley & Votruba-Drzal, 2012). African Americans are found to be more likely to use center care than White and Latino families regardless of family income (Cappizzano et al., 2006), while Latinos have the lowest preschool enrollment rate among the three racial groups, even within the same income strata (Brown-Lyons et al., 2001; Collins & Ribeiro, 2004; Fuller et al., 1996; Liang et al., 2000; Magnuson & Waldfogel, 2016). With regards to aspects of preferred care, Barbarin and colleagues (2006) found ethnic differences in the parental definition of quality. White parents often cite emotional climate of the classroom as a factor in their choice, while African American parents care about home-school partnerships and close relationships with staff.

However, other studies show that after controlling for family socio-economic and child characteristics, race and ethnicity is not a significant predictor of childcare choices. For example, Delgado (2009) finds that Latinos and non-Latino White parents do not differ in their use of care. Grogan (2012) assessed parents' considerations to enroll in state pre-K programs and found that parents' traditional and progressive beliefs about childrearing and parents' involvement at home and school do not affect their quality and practical considerations about state pre-K program differently by race or ethnicity.

The existing literature offers some possible explanations for the inconsistent findings about the effects of race and ethnicity on childcare choices. First, racial/ethnic differences may reflect mean differences in family socio-demographic characteristics. For example, African American and Latino families may be more likely to fall on the lower end of the socioeconomic spectrum, and socio-economic status has stronger predicting power than race and ethnicity in explaining the variation in childcare choices (Early & Burchinal, 2001; Grogan, 2012). When it comes to parental employment, African American mothers with young children are more likely to work full time than White mothers, while Latino mothers are less likely to be employed (Fox, Folk, & Beller, 1993).

Second, families may vary in the degree to which they maintain their own cultural values and beliefs when choosing childcare, as well as the extent to which their parenting beliefs and practices at home align with wider societal norms. For example, home language is considered as an indicator of family integration in society. Latino parents who primarily speak English at home follow closely the childcare choice patterns of White middle-class families (Liang et al., 2000). Latino parents who speak Spanish at home, along with members of language minority groups, are less likely to choose center care (Fuller et al., 2002; Liang et al., 2000).

2.2.1.6 Child attributes

The final factor in the *resources and needs* domain that affects parental decisions about childcare choice is the child him/herself (Crosnoe et al., 2016). From a child development and developmental psychology perspective, the interaction between the child and his/her environment is considered bidirectional (Bronfenbrenner, 1981; Darling & Steinberg, 1993; Kuczynski, 2003). The idea is that children can act as agents in their development within the family influences (Cummings, Davies, & Campbell, 2002), and are capable of affecting parents' behaviors, and, subsequently, the environments they live in (Bell, 1968; Bell & Harper, 1977; Belsky, 1984). In the childcare choice context, the traits and behaviors of young children draw responses from parents who are sensitive to their child's age, level of development, and temperament when making childcare decisions (Casper, 1996; Coley, Votruba-Drzal, Collins, & Miller, 2014; Crosby, Gennetian, & Huston, 2005; Fuller et al., 2002; Gamble, Ewing, & Wilhlem, 2009; Greenberg, 2011; Lowe & Weisner, 2004).

In terms of selecting childcare to best fit the child, Crosnoe and colleagues (2016) proposed that parents may have two seemingly opposite considerations—compensatory elicitation or enrichment elicitation. Compensatory elicitation refers to purposefully selecting the type of care to help the child who is developmentally delayed or difficult to manage. For example, Sandstrom and Chaudry's interviews (2012) with low-income urban working mothers reveal that parents of children with special needs often select care arrangements to meet their children's therapy needs more than their own scheduling or employment needs or other logistics. Enrichment elicitation, on the other hand, refers to the selection of care that could meet the developmental needs of the child who is more developmentally advanced (Clarke-Stewart & Allhusen, 2005; Grogan, 2011; Pianta & Walsh, 1996), for instance, by enrolling them in preschool earlier than four years old (Greenberg, 2011).

2.2.2 Preferences and perceptions

Beyond these family-level attributes that are generally observable, the second domain includes family *preferences* for certain type of care and *perceptions* of available childcare options within their communities (Chaudry et al., 2011; Fuller, Holloway, Rambaud, & Eggers-Pierola, 1996; Uttal, 1999). This set of studies provide insights into more intangible aspects that may affect parents' childcare choice decisions, such as parents' ideas about their childcare options in terms of what parents think they have access to, what they consider high quality, and what they feel best meets the needs of their family and the child. With data collected from nationally represented samples, or interviews and surveys with parents sampled from smaller geographic units, these studies reveal that parents have different preferences and perceptions over different types of childcare arrangements. Unlike most measures in the *resources and needs* domain, measures in this domain are often unobservable to the researcher.

2.2.2.1 Preferences

Preferences refer to parental priorities regarding desirable characteristics of childcare alternatives based on values and beliefs about parenting and the child's development (Coley, Votruba-Drzal, Collins, & Miller, 2014; Grogan, 2011; Lowe & Weisner, 2004; Shlay, Tran, Weinraub, & Harmon, 2005). Among parents who place emphasis on the educational benefits of preschool, they often value program components such as providers with education and training, promoting social skills, and a structured curriculum (Early & Burchinal, 2001; Gamble et al., 2009). Parents who prioritize family over work use less non-parental care arrangements, and when they do need childcare, they are less likely to use formal preschool (Huston et al., 2002). Certain parents prefer relative or friend care because trust is important to them. They trust relatives or friends more than center-based caregivers for reasons such as similar childrearing practices, same home language, and ease to communicate with (Chaudry et al., 2011; Fuller, Kagan, Suzuki, & Chang, 2001).

2.2.2.2 Perceptions

Perceptions refer to parents' assessments of the local childcare market with regards to the affordability and accessibility of available childcare options under more practical considerations (Meyers & Jordan, 2006). These perceptions may or may not be accurate due to the lack of comprehensive information to know all available options and/or know the options well. This may be due to several reasons: parents are content with their current care arrangement and therefore do not need to explore other care options; parents lack personal contacts with experience or knowledge of childcare options; or, parents do not have information about or access to local agencies to apply to and secure public assistance. In addition, parents may not be able to seek information about childcare options due to barriers to access information, such as language and literacy, time pressures, or family obligations (Chaudry et al., 2011). Regardless of the accuracy, parents' perceptions of their neighborhoods are believed to affect how they interact with institutions or resources in their neighborhoods (Sharkey & Sampson, 2010). It is possible that parents may not seek any preschool if they do not think they have good options nearby, and instead, rely on informal care arrangement. Parents' perceptions of childcare options, unlike preferences, tend to involve more practical considerations. For example, center-based care, despite being viewed positively for its educational benefits, is often perceived by low-income parents either as too expensive to afford (Head Start and state pre-K are basically free program for income eligible families) or too restricted to meet parents' schedule needs (Chaudry et al., 2011; Crosnoe et al., 2016; Fuller et al., 2002).

2.2.3 Mismatch

Given the complex set of factors parents take into consideration when making childcare choices, it is not surprising that parents often express a mismatch between the type of care they preferred and the type of care they use (Buriel & Hurtado-Ortiz, 2000; Hirshberg et al., 2005). This has several implications. To begin with, as discussed in section 2.1.1 (early childhood policies in the U.S.), the nature and purposes of childcare alternatives defined by federal, state and local policies differ, which could restrain the childcare choice set available and accessible to individual families (Baum, 2002; Urban & Olson, 2005). Next, it may indicate that childcare choices are often constrained by family resources and needs. For example, parents have to balance between preferences and more practical considerations, such as childcare cost, location, schedule, and convenience. On the other hand, this mismatch could also indicate a shortage of or barriers in access to certain childcare options experienced by different groups (Barbarin et al., 2006; Fuller, Holloway, Rambaud & Egers-Pierola, 1996; Morrissey, 2008; Queralt & Witte, 1998; Rose & Elicker, 2010).

To date, no study has empirically tested the direct effect of childcare supply on family childcare choices at the family level. With this in mind, I now turn to differential patterns in childcare choices made by immigrant and U.S.-born parents and barriers that may explain the preschool enrollment gaps (section 2.3), before I discuss in more detail how this study fills the gap in our current understanding of the relationship between community-level childcare supply and family-level childcare choices (section 2.4).

2.3 Uneven Access to Preschool by Parental Immigration Status

Similar to those examining childcare choices in general, studies of immigrant families' childcare choices have focused on factors at the family level—family characteristics, immigration contexts, as well as cultural preferences—that facilitate or hinder the use of center-based care for preschool-aged children growing up in immigrant families. These studies, in general, have found that children of immigrants have lower preschool enrollment rates than children of U.S.-born parents (section 2.3.1). This gap in preschool enrollment by parental immigration status has been explained by a set of barriers including a lack of financial, human, and social capital, cultural preferences, a lack of childcare supply, and information barriers (section 2.3.2). Overall, the factors discussed in the previous *resources and needs* domain apply to the immigrant context and affect childcare choices in similar ways.

2.3.1 Childcare choice patterns among immigrant families

Most studies exploring the childcare choices of immigrant families compare differences in childcare choice patterns between immigrant and U.S.-born parents, revealing that children of immigrants have lower rates of participation in any type of non-parental care, including center care (Capps, Fix, Ost, Reardon-Anderson, & Passel, 2004a; Karoly & Gonzalez, 2011; Matthews & Ewen, 2006). Despite research efforts to detangle the immigrant effect on childcare choices over other variables, such as region/country of origin, parental citizenship status, legal status, time in the country, immigration generational status, and English proficiency (Cannon, Jacknowitz, & Karoly, 2012; Crosnoe, 2007; Ha & Ybarra, 2014; Miller, Votruba-Drzal, & Coley, 2013; Turney & Kao, 2009; Vesely, 2013; Yesil-Dagli, 2011), the disparity in preschool enrollment during the pre-K year has been persistently evident over time and across several nationally representative data sets, such as the ECLS-K (Crosnoe, 2007; Magnuson et al., 2006; Turney & Kao, 2009), the 2005 National Household Education Survey (Kahn & Greenberg, 2010), the ECLS-B (Miller et al., 2013), the Head Start Impact Study (Greenfader & Miller, 2014), and the SIPP panel data (Brandon, 2004).

2.3.2 Barriers in access to preschool among immigrant families

Findings from empirical studies on childcare choices, combined with interviews with immigrant parents, highlight a set of factors and/or barriers that immigrant families struggle with when looking for childcare. Some barriers, such as *lack of financial, human, and social capital*, *informational barriers,* and *lack of childcare supply*, affect disadvantaged immigrant children in similar ways as they affect their similarly disadvantaged counterparts with U.S.-born parents. The other, *cultural preferences,* may be common to certain racial groups regardless of immigration status.

2.3.2.1 Lack of financial, human, and social capital

While there is considerable heterogeneity among the immigrant population on average, children growing up in immigrant families often face several developmental risk factors common to low-income families in general, such as economic disadvantages, lower levels of parental educational attainment, neighborhood poverty and segregation, social network with other poor (often immigrant) residents, and lack of transportation. Among them, income is speculated to contribute the most to the differential access to center-based care among immigrant families as a whole (Booth, Crouter, & Landale, 1997; Hofferth, 1999). In 2014, poverty (defined as below 200% of the federal poverty threshold) affects 55% of children age six and under living in immigrant families, compared to 44% of peers with U.S.-born parents (Jiang, Ekono, & Skinner, 2015).

In addition to risk factors common to low-income families in general, two unique human capital disadvantages for immigrant parents—limited English proficiency and status (either legal or illegal)—may further deprive immigrant families of access to center care. Although parental English proficiency varies by the parent's country of origin, ranging from nearly 100% among Canadian immigrants to less than 40% among Mexican immigrants, more than one out of four immigrants live in linguistically isolated households, meaning no one over the age of 13 speaks English exclusively or very well (Hernandez, Denton, & Macartney, 2009). The influence of language barrier goes beyond the linguistic skills parents impart to their children. First, limited English proficiency is found to have negative effects on immigrants' access to other human services (Brown at al., 1999). Second, parents who are English language learners are less likely than fluent English speakers to find full-time, stable, and better-paid jobs. Similarly, in regard to the parental immigration status, children of undocumented parents are significantly less likely to use center care out of fear of deportation (Ha & Ybarra, 2014; Karoly & Gonzalez, 2011). Distrust of government programs is also common among undocumented immigrants (Karoly & Gonzalez, 2011).

Last but not least, immigrant parents' financial, human, and social capital, along with cultural norms and preferences, may affect their comfort level with formal care providers. Immigrant parents, in general, are less familiar with the U.S. education system. What can further amplify the discomfort associated with this unfamiliarity are the parents' own educational attainment, English proficiency, and legal status. Immigrant parents who have little schooling, limited English proficiency, or are undocumented may feel intimated by preschool teachers and staff who speak English, so they may avoid using center-based care at all.

Moving beyond the individual-level attributes that put immigrants at disadvantage for choosing formal childcare, certain groups of immigrants are more likely to live in inner-city or ethnically segregated neighborhoods with fewer social services (Borjas, 1999). This may have negative impact on the families (Ficano, 2006). On the individual level, with the concentration of similarly low-income, less educated immigrants, immigrant families with young children living in these communities often don’t have the needed social capital to navigate the childcare market. On the structural level, the limited childcare supply in poor communities where some groups of immigrants tend to concentrate can not meet their childcare needs for flexible hours, subsidized spaces, or bilingual or culturally competent staff (Adams & McDaniel, 2009; Karoly & Gonzalez, 2011).

2.3.2.2 Cultural preferences

One reason often cited to explain the lower enrollment rates in preschool among immigrant families is that immigrants from many parts of the world adhere to their home country's familial values (Portes & Rumbaut, 2001). Sociocultural theories of development suggest that immigrant parents may have culturally-specific beliefs about non-parental care and child development that give rise to differences in care use (Bornstein & Cheah, 2006). For example, some immigrant parents desire a continuity of culture and language that recreate their own social experiences for their children. As a result, there may be a preference for parental care among immigrant families to promote the children’s ethnic and cultural identities (Hernandez, 1999; Booth et al, 1997; Brandon, 2002), and greater trust for co-ethnic caregivers (Miller et al., 2013, 2014; Obeng, 2007; Vesely, 2013), and/or relatives that provide culturally similar practices (Brandon, 2004; Hirshberg et al., 2005; Lowe & Weisner, 2004).

2.3.2.3 Informational barriers

Given the lack of financial, human and social capital and cultural preferences discussed above, it is not surprising that many immigrant families may be less resourceful than their U.S.-born counterparts of childcare services available in their communities or unaware of public assistance they are eligible to receive (Adams & McDaniel 2009; Matthews & Jang 2007; Obeng 2007; Perreira et al., 2012). They may also have misconceptions which can negatively affect enrollment in formal care arrangements (Brandon, 2004; Fix & Passel, 2002; Karoly & Gonzalez, 2011; Liang, Fuller, & Singer, 2000; Matthews & Ewen, 2006), such as stigma associated with public assistance dependence, fear of deportation, and perceived preschool cost even for programs that are no- or low-cost (Brandon, 2004; Fix & Passel, 2002; Karoly & Gonzalez, 2011; Liang, Fuller, & Singer, 2000; Matthews & Ewen, 2006). Matthews (2010) implies that immigrant families may mistakenly equate using federal benefits, including childcare assistance, to being a public charge, which in turn, could potentially affect their application for permanent residency or citizenship or the family's eligibility to bring other family members to the U.S. To the contrary, accessing childcare subsidies is not considered in making a public charge determination, and the receipt of public benefits does not affect eligibility for citizenship (U.S. Department of Justice, 1999).

2.3.2.4 Lack of childcare supply

While it is true that family-level attributes discussed above help explain lower participation rates in preschool among immigrant families, a handful of studies, most of which are interviews and surveys, directed the attention to the supply side of childcare which also casts constraints on childcare choices, especially center participation. These studies reveal that lower preschool participation rates could be attributable to a lack of affordable, accessible center care in immigrant communities, rather than a preference for relative care (Matthews & Jung, 2007; Calderon, 2007; National Task Force on Early Childhood Education for Hispanics, 2007).

In a survey study, Buriel and Hurtado-Ortiz (2000) find that foreign-born Hispanic mothers would have liked to increase center use had there been more child centers available. Uttal (1999) discovers that African and Hispanic American families with extensive nearby family networks are more likely to use relative care. Hirshberg and colleagues' interviews (2005) with Hispanic parents from three California counties reveal that parents in neighborhoods with more available center-based care slots are more likely to use it than not. Similarly, Greenfader and Miller (2014) suggest that, if randomly assigned a spot in Head Start, Spanish-speaking dual language learners were more likely than monolingual-English children to attend it. Although their samples were not nationally representative (Buriel & Hurtado-Ortiz, 2000; Hirshberg et al., 2005; Uttal, 1999), nor is the scope of childcare studied comprehensive of all childcare types, these studies inspire me to empirically explore the supply side of the childcare market and its role in determining childcare choices among immigrant families.

2.4 Justification of the Present Study

While researchers continue to explore why childcare choices vary and how they vary systematically by different immigration context, it is evident that the current literature tends to view parental immigration status and other immigrant indicators simply as contributing factors into the childcare choice decision. It does not sufficiently disentangle the multifaceted nature of being immigrant parents in the childcare choice context. These studies are limited with regards to three aspects, which I will address in this study—lack of a more realistic framework (section

2.4.1), need for a more comprehensive data set (section 2.4.2), and a more appropriate empirical model (section 2.4.3).

2.4.1 Need for a new conceptual framework

As discussed earlier, the reality facing families in need of childcare is more complex than what a set of observed family-level attributes can describe, an approach commonly used in developmental psychology. Similarly, when adding the immigrant context into the childcare choice context, there is a need for a more thoughtful framework rather than just including immigrant indicators (parental immigration status, region of origin, etc.) into the childcare choice equation. I would speculate that this common approach to handle the immigrant context in the current childcare choice literature is in part due to the lack of a more comprehensive and realistic approach accounting for the supply side to begin with.

This study addresses the complexity by building upon the heterogeneous availability of alternatives framework from the field of labor economics. It also addresses the lack of an appropriate immigration theory in the immigrant childcare choice literature by adapting the spatial assimilation framework. The heterogeneous availability of alternatives framework acknowledges the constraints individuals often face when making decision among a set of choice alternatives, which is often individual specific, random, and latent. It is applicable to the childcare choice situation wherein parents, acting as decision-makers, have access to only a limited set of childcare alternatives as a result of family attributes, preferences, and supply constraints.

The spatial assimilation theory posits that children of immigrants' socioeconomic outcomes are in part affected by the residential locations their immigrant parents settled in. The emphasis on geography linking the immigrant residential location to perceived opportunities and constraints for children of immigrants is relevant for the problem of childcare choices among immigrant families, where access to formal childcare or lack thereof can be viewed as opportunities or constraints to the benefits of preschool education. In this framework, parental immigration status and its impact on childcare choices are characterized as resulting from the residential location immigrant parents choose.

2.4.2 Data limitations

Constraining researchers' abilities to study childcare choices is data availability in the field of early childhood education. Most studies that examine childcare choices lack measures of the supply. While the commonly used ECLS data sets include a rich set of family- and child-level characteristics from nationally representative samples, they do not provide much information on the supply of childcare. Data from individual states often do incorporate condition of the childcare supply within the state (e.g., Hatfield et al., 2015; Herbst & Barnow, 2008); however, studies that use them often lack information of individual families and their actual childcare choices. As a result, our ability to study the link between the childcare supply and family childcare choices has been limited.

A second issue related to data limitations has been the use of proxy variables in the study of childcare supply. There have been efforts to use proxy variables for specific childcare alternatives, but they are less than ideal. One common practice to study the influence of the supply side is to use the number of childcare workers in a center setting or in a licensed family childcare home, collected by the Census Bureau, as proxy for the supply of available center or family childcare homes within a specified geographic location (Tang et al., 2012). It rises two issues. First, this proxy can not tell us the capacity (available slots) of centers or family childcare homes within the family's proximity, because the teacher-child ratios vary by age and care type under state and local contexts. In addition, when it comes to measuring individual care providers, it has always been difficult to capture measures that proximate their availability, such as the number of individual provider locations (Herbst & Barnow, 2008).

Another proxy variable researchers have used for childcare supply is public funding levels (Greenberg, 2010; Magnuson et al., 2007). However, this measure can be problematic too when used in cross-state studies, because it assumes that state pre-K slots are funded with equal amounts across states. States vary greatly in their per-pupil expenditures for state pre-K. Even when studying pre-K within the same state, most studies do not differentiate the amounts of public funding allocated, which may vary by community characteristics, and assume instead that public funded preschool spots are equally distributed across communities regardless of the local socio-economic conditions. In addition, states' expenditures on state pre-K programs do not necessarily correlate with the number of state pre-K slots because some expenditures may be targeted at quality improvement or integration efforts to link pre-K data with K-12 data, rather than program expansion. Therefore, state funding may not be a good indicator for the quantity of state pre-K provision at the community level.

In this study, I used physical locations of state pre-K and Head Start, in addition to supply measures of other childcare alternatives (discussed in Chapter 4), to reflect the density of service provision each parent has access to within the community. This addressed data limitations in two ways. First, I created a comprehensive data set that has measure for each childcare alternative. Second, this supply-side measure can be linked to family-level attributes, allowing me to study how supply affects childcare choices.

2.4.3 Methodological constraint

In addition to data limitations that may have constrained the ability of prior research to link childcare supply to individual families' childcare choices, there is a need for an empirical model that can account for supply-side attributes, such as the number of service providers, and the real choice situation. Among existing studies, researchers have predominantly employed the multinomial logistic model (MNL) to predict childcare choices. Similar to constraints cast by data limitations, the MNL does not control for attributes of the choices themselves. In other words, using an MNL approach, one could only predict childcare choices based on family-level attributes. In this study, I used a conditional logit model (CLM) to address this issue. From a conceptual perspective, the CLM is a discrete choice model that allows me to account for attributes of the choice alternatives, which may be individual specific and vary across alternatives. From a methodological perspective, it is also subject to fewer assumptions than the MNL model, as described in more detail in Chapter 4.

CHAPTER 3: CONCEPTUAL FRAMEWORKS

As summarized in Chapter 2, the framework commonly used to describe childcare choices conceptualizes them as the result of family and child needs, financial resources, social and cultural expectations, as well as preferences and perceptions of local childcare options (Buriel & Hurtado-Ortiz, 2000; Chaudry et al., 2011; Crosnoe et al., 2016; Meyers & Jordan, 2006). An implicit assumption in most of these previous empirical studies examining childcare choices is that the family is free to choose any childcare arrangement conditional on the family and child attributes. This strand of thought derived from developmental psychology was challenged by a few studies which reveal that immigrant parents would also like to enroll their children in center-based care had there been enough supply in their communities (Buriel & Hurtado-Ortiz, 2000; Greenfader & Miller, 2014; Hirshberg et al., 2005). This requires a comprehensive and more realistic framework that can explain the complexities associated with immigrant parents' childcare choices.

In this study, I adapted two frameworks—heterogeneous availability of alternatives from economics and spatial assimilation from sociology—to re-conceptualize the childcare choice problem within the immigrant context. The term *heterogeneous availability of alternatives* was first introduced in labor supply analysis (Aaberge, Colombino, & Wennemo, 2009). This framework acknowledges two aspects in any choice situation: (1) the observed attributes of the decision-maker, and (2) the set of alternatives with latent attributes available to the decision-maker. In my view, it presents a more comprehensive approach to study choice situations where the decision-maker and his/her choice set are bounded by attributes of both the supply and demand sides.

The tie between the supply condition and immigrant families is the residential location. I adapt the *spatial assimilation* theory from sociology to study the potential differential effects of childcare supply on family-level childcare choices by parental immigration status. From a broad perspective, the spatial assimilation theory explains varying degrees of residential integration into U.S. society among immigrants (Portes & Zhou, 1993), especially how where immigrant parents choose to reside affects their children's social mobility (Goodwin-White, 2016).

Together, these two frameworks link community characteristics which may be systemically different between immigrants and U.S.-born individuals (spatial assimilation theory), the latent specific sets of childcare alternatives to individual families (heterogeneous availability of alternatives framework), and families and child characteristics, to family-level childcare choices during the pre-K year. In sections 3.1 and 3.2, I discuss the heterogeneous availability in alternatives and spatial assimilation frameworks, respectively, and their application in this study. I end this chapter with hypotheses based on each specific framework in section 3.3.

3.1 Heterogeneous Availability in Alternatives (HAA)

Heterogeneous availability in alternatives (HAA) is an empirical approach extended from the traditional labor supply analysis (Aaberge, Colombino & Wennemo, 2009), one field where general choice behavior theory applies (McFadden, 1973). This approach acknowledges constraints individuals often face when making decisions among a set of choice alternatives which are individual-specific, random, and latent (section 3.1.1). It is applicable in other choice situations, including the childcare context (section 3.1.2).

3.1.1 Origin in labor supply analysis

Initially proposed by Dagsvik and Strøm (1992) and adapted by Aaberge, Dagsvik, and Strøm (1995), the term *heterogeneous availability of alternatives* did not appear until recently in labor supply analysis (Aaberge, Colombino & Wennemo, 2009). The traditional approach used to understand labor supply assumed that individuals were free to choose whether or not to work/or their preferred hours of work. Dagsvik and Strøm (1992), however, observed an extreme concentration of employment around full-time and part-time hours. They remarked that this indicated important constraints on employment hours *offered* in the labor market (Dickens & Lundberg, 1985). In other words, individuals faced constrained employment choices. They then argued that the conventional approach focusing solely on the influence of individual preferences in labor force participation did not fit the data. There was a shift analytically to start including *choice environment* in describing labor force participation decisions. The choice environment, as the supply side is often called in the labor supply literature, is comprised of a number of job opportunities, also called matches. Each match corresponds to a particular combination of skills required to perform certain tasks or activities, and characteristics of the job such as hours of work, wage rate and non-pecuniary attributes. What had made it difficult to model for earlier labor supply researchers was that the set of matches was viewed as individual specific, random, and latent, as described below.

The set of matches is *individual specific* because individuals vary by qualifications and preferences over specific job attributes and job opportunities differ by qualifications required and other characteristics. One can also consider labor supply as the result of the decision-maker's choice from a set of job packages. Each package is characterized by an offered wage rate, offered hours of work, and nonpecuniary attributes describing the nature of the job-specific tasks to be performed (Dagsvik & Strøm, 1992), such that employment positions with the same tasks to be performed but with different working hours are viewed as different jobs (Dagsvik & Jia, 2008). Therefore, the set of job matches differs across individuals.

According to the choice behavior literature in general, econometricians also consider this set of matches to be *random* in two aspects. On the one hand, the parameters representing choice sets are viewed as random effects. The traditional approach interpreted it as capturing the random variation in preferences across individuals and job opportunities due to attributes unobservable by the researchers (but perfectly known to the decision-makers). On the other hand, individual preferences themselves are viewed as random. It follows that individuals may make different choices when presented with identical choice settings on each occasion (Tversky, 1969) because the decision-maker may have insufficient information about or inaccurate perceptions or experience with the choice alternatives. Accordingly, they may find it difficult to make a precise assessment of their utility once and for all.

What further complicates the matter is that, the set of matches is not only individual specific and random, but also *latent*. This is because the researcher usually has very little information about individual-specific preferences about job opportunities, or the attributes of all job opportunities available to the decision-maker. There is of considerable interest in many empirical applications where the researcher cannot observe each decision-maker's choice set, but can only observe some attributes of the chosen alternative. For example, in his seminal work examining residential location, McFadden (1974) stated that it was difficult for the researcher to have information on the choice alternatives available to the decision-maker, including the different communities being considered, their respective school quality, crime rate, and convenience to work/grocery. All he had were data on the chosen residential location and its characteristics.

Aaberge and colleagues (Aaberge et al., 2000, 2009) and Dagsvik and colleagues (Dagsvik & Jia, 2008; Dagsvik & Strøm, 2006) later extended this choice alternative or match framework to include the quantity of choice alternatives. They argued that there were important quantity constraints in the market, in the sense that different types of jobs are not equally available to every agent. Using the hours of work as an example, Aaberge and colleagues (Aaberge et al., 2000; Aaberge, Colombino, & Strøm, 1999; Aaberge et al., 1995) assumed that all the hour opportunities are in principle available, but not equally accessible for everyone. Together, the choice environment framework combined with the attributes of choice alternatives is referenced to as the *heterogeneous availability of alternatives*.

To summarize, the HAA highlights the complex dynamics between the decision-maker and the choice set, as well as the importance of the match between the two, which is individual specific, random, and latent. This approach better conceptualizes the "true" choice environment, because it takes into consideration (1) the attributes of choice alternatives, often unobservable and heterogeneous, and (2) the decision makers' attributes (observable) and preferences (unobservable).

3.1.2 Application in childcare choice context

The challenge facing early researchers in the field of labor supply is the same we face in childcare choice analysis where attention has focused on examining attributes of the decision-makers themselves. Essentially, these studies followed the underlying assumption that there was no variation in the choice environment. This is inconsistent with the lack of center care options expressed by some immigrant families (Buriel & Hurtado-Ortiz, 2000; Chaudry et al., 2011;

Crosnoe et al., 2016; Meyers & Jordan, 2006). If we consider the extreme concentration of full-time or part-time employment offered in the job market, the observation early labor supply researchers made, as lacking access to employment opportunities with alternative hour configurations, then it makes an appropriate analogy to the current childcare data which failed to explain if choosing childcare alternative other than center care, the preferred type, reflects a lack of supply to certain families. The HAA framework, therefore, is consistent with a story where childcare choice decisions rely on both family-level attributes (including preferences) and the choice environment constraints. There are some nuances between the childcare choice and labor supply contexts, though, mainly due to the nature of the problem and data availability. These differences in supply, attributes of choice alternatives, and dimensions of match, are summarized in Table 3. 1 and discussed below.

3.1.2.1 Supply

Supply refers to the ideal set of choice alternatives in the economy. In the childcare choice context, the supply consists of <u>six</u> mutually exclusive childcare alternatives: parental care, individual providers, licensed FCC home, center care, state pre-K, and Head Start. In the context of labor supply analysis, supply refers to the job opportunities on the job market. Unlike the childcare context where the number of each childcare choice alternative can be measured (I will describe these measures in Chapter 4), it is difficult to derive a definite number of job opportunities because researchers do not know job-specific attributes or the job search scope (e.g., national vs. local). In addition, unlike the six mutually exclusive childcare alternatives, there is not a commonly agreed upon categorization of job opportunities.

Table 3. 1 Comparison of contextual and conceptual differences between childcare choice and labor supply contexts

Context	Supply	Attributes of choice alternatives	Dimensions of match
Childcare Choice	Childcare alternatives (ideally, six mutually exclusive alternatives)	Quantity; sector (private vs. public); formal vs. informal; cost; hours of operation; convenience; quality; age of children cared for, etc.	<u>*Preference*</u>: Match between family preferences and attributes of childcare choice alternatives <u>*Affordability*</u>: Match between family budget and childcare cost; match between eligibility and family attributes <u>*Accessibility*</u>: If location is convenient (local)
Labor Supply	Job opportunities (unobserved quantity)	Hours of work; wages; other non-pecuniary attributes; qualification required to perform the tasks/activities; etc.	<u>*Preference*</u>: Match between individual preferences and attributes of job opportunities <u>*Qualification*</u>: Match between individual qualifications and qualification required by job opportunities; <u>*Accessibility*</u>: Scale of job market could range from local to national

3.1.2.2 Attributes of choice alternatives

Attributes of choice alternatives are specific characteristics of the choice alternatives. In the childcare choice context, these characteristics often include but are not limited to quantity (number of providers within each childcare alternative), sector (private vs. private), formal or informal care arrangement, cost, hours of operation, location/convenience, quality, ages of children cared for, etc. In the labor supply context, these characteristics often include hours of work, wage, qualifications required to perform the tasks or activities, and other non-pecuniary attributes of the job opportunities.

These attributes vary across and within choice alternatives. For example, hours of operation differ by childcare alternative. Childcare centers often operate 12 hours a day to accommodate the schedule needs of working parents, while some state pre-K classroom or Head

Start centers operate on half-day schedules. Even within the same childcare alternative, individual care providers, for example, may differ with regards to teacher qualifications, hours of services, proximity to work/home, etc. As a result, this creates individual specific sets of matches between the parents and the childcare alternatives.

3.1.2.3 Dimensions of match

As discussed above, the set of matches is individual specific, latent, and often random as a result of the complex decision-making process. They can be conceptualized as considerations under three matching dimensions: preference, qualification (affordability), and accessibility. They simultaneously cast constraints on the number of matches available to the decision-maker, such that even if a match can be established under one dimension, it can still be affected after considerations under the other two dimensions.

To begin, the *preference* dimension is arguably the most straightforward in both the labor supply and the childcare choice contexts. The dimension has also been extensively studied in the childcare care literature, as summarized in Chapter 2. Setting aside issues of qualification (affordability) and accessibility, the decision-maker enters the market with a set of a priori preferences for specific attributes of the choice alternatives. In the labor supply market, the decision-maker may prefer certain hours of work and wage ranges, for example. In the childcare choice context, decision makers may prefer attributes related to quality, curriculum, and hours of operation, among others. Preferences can be viewed as random when decision-makers have insufficient information or inaccurate perceptions about the choice alternatives.

Individuals also vary by *qualifications,* which, in the labor market, makes them either qualified or not for the available job opportunities with specific tasks and activities to be performed. This is where the choice alternatives (job opportunities) themselves, rather than the decision-maker him- or herself, cast constraints on the choice set. In the context of childcare choice, it is the family's income and the eligibility requirements of certain childcare alternatives that reduce the number of matches between the family and the childcare alternatives. Families differ with respect to the amount of budget that they can allocate for childcare expenses. When the cost of certain childcare alternative(s) exceeds the allocation, the *affordability* of these childcare alternative(s) becomes problematic. On the other hand, certain childcare alternatives have eligibility requirements. Even though they are publicly funded (therefore not a constraint for families with limited childcare budget), the eligibility requirements exclude certain families from using these childcare alternatives.

Finally, *accessibility* refers to whether the decision-maker has access to the location(s) of the choice alternative(s). There is a slight difference between parents making childcare choice and job seekers looking for employment opportunities. In the childcare choice context, parents tend to choose childcare locations that are either near home or close to work. As such, it is possible to define a geographic area as the local market within which the parents are most likely to make childcare choice decisions. That is to say, the local market of childcare alternatives is observable geographically. In the labor supply context, however, the scope of job search can range from local to national. This makes it difficult for the researchers to know all the job opportunities the decision-maker may be considering or qualified for.

Together, the complex decision-making process involving considerations under the three dimensions confirm that the heterogeneous availability in alternatives framework is an appropriate and comprehensive model to explain the childcare choice context.

3.2 Spatial Assimilation

The spatial assimilation theory stresses how integration depends upon immigrants' settlement patterns and existing patterns of racial or ethnic residence (Alba, Logan, & Stults, 2000; Logan, Alba, Mcnulty, & Fisher, 1996). This focus on residential geography has not usually been at the forefront of research on immigrants and their children, but provides a lens for integrating characteristics of the residential locations into which immigrant families make childcare choice decisions. While earlier studies have focused on varying patterns of assimilation across different ethnic groups (Massey & Denton, 1987), or assimilation patterns specific to different geographic units among the immigrant parents (Alba, Logan, Stults, Marzan, & Zhang, 1999; Waldinger, 1996) (section 3.1.1), recent theoretical developments in spatial assimilation focus on groups' socioeconomic outcomes in relation to the settlement locations of earlier generations (Goodwin-White, 2016). In other words, the settlement locations are perceived as either opportunities or constraints in the social mobility of children born to immigrant parents (section 3.2.2). I adapt this theoretical framework, which has not yet been applied widely in immigrant studies, to examine young children of immigrants in terms of the opportunities they have to childcare options (section 3.2.3).

3.2.1 Background

The spatial assimilation theory is one thread of the segmented assimilation theory used to study the integration of immigrants in the U.S. and their diverse outcomes (e.g., Haller, Portes, & Lynch, 2011; Hirschman, 2001; Kao & Tienda, 1995; Hao & Pong, 2008; Portes & Zhou, 1993; Waldinger, Lim, & Cort, 2007; Xie & Greenman, 2011). It asserts that as immigrants interact with members of the White middle class, the initial disadvantages associated with the immigrant status should eventually be reduced leading to more increased residential integration (Massey, 1985; Massey & Denton, 1985).

The degree of spatial assimilation is believed to reflect the level of cultural and economic integration (Massey, 1985). Residential mobility into neighborhoods with greater percentages of non-Hispanic Whites increases as immigrants build up more human and financial capital and become more proficient in English language use (Denton & Massey, 1988; South, Crowder, & Chavez, 2005). In other words, as immigrants accrue more economic resources over time, they are believed to have more choices with regard to their residential locations (White, Biddlecom, & Guo, 1993).

Spatial assimilation theory has been applied in various studies that demonstrate the complex interaction between location and immigrants, which vary by ethnicity, urbanicity, immigration cohort (age of migration to the U.S.), and income. Using individual-level data from the 1970s-1990s, studies have focused either on varying degrees of residential segregation across different *ethnic groups* (Massey & Denton, 1987; South et al., 2005; White et al., 1993), or on the varying degrees of assimilation patterns specific to varying levels of *urbanicity*, such as urban areas (Waldinger, 1996) or the suburbs (Alba et al., 1999). In addition to ethnicity and urbanicity, immigration cohort and income further add variation to the assimilation patterns. For example, Allen and Turner (1996) discover that assimilation patterns differ within the same ethnic group by *immigration cohort*, and greater variation was found between locations among higher *income* immigrants.

3.2.2 Geographic dispersion and social mobility

Moving beyond examining the assimilation patterns of the immigrants themselves, recent studies claim that the location choices of immigrant parents affect their children’s socioeconomic outcomes. It follows the ideas that geographic dispersion facilitates social mobility, and that characteristics of the ethnic environment enable or constrain progress (Vigdor, 2008). For example, higher immigrant concentration and their educational attainment are positively associated with the wages and educational outcomes of a second generation 30 years later (Goodwin-White, 2016). Therefore, it makes sense to state that the second generation's socioeconomic outcomes depend in part on the location choices and characteristics of a previous immigrant generation.

3.2.3 Residential location and childcare choices

The location-specific focus of the spatial assimilation theory that links immigrant residential location to opportunities and constraints is applicable to the topic of childcare choices among immigrant families. Having access to formal childcare, such as center-based care (childcare centers, state pre-K, or Head Start), can be viewed as an important educational opportunity (or constraint if lack thereof) for children of immigrants, because center participation is often associated with better school readiness levels and economic outcomes later in life. Therefore, I adapt the same theoretical thinking (Goodwin-White, 2016; Vigdor, 2002) in asking whether and how immigrants' residential location affects their children's development through opportunities (access to) and constraints (lack of access) in childcare choices.

3.3 Hypotheses

Together, the heterogeneous availability of alternatives and the spatial assimilation frameworks allow for a conceptual linkage between the community (immigrant residential location), its characteristics, and the supply of childcare alternatives and the childcare choices of immigrant families. The goal of this study was to test whether and how parental childcare choices are facilitated or constrained by community-level childcare supply, as measured by the quantity of each childcare alternative, and parental immigration status.

With regards to how the childcare supply compares by parental immigration status (question 1), I had two hypotheses. First, less affluent communities tend to have fewer formal childcare arrangements. As discussed earlier, immigrants are more likely than U.S.-born counterparts to live in poverty, therefore, I hypothesized that *immigrant families overall live in communities that offer less access to preschool*. I expected to see less variation in the number of childcare supply between immigrant and U.S.-born parents within certain income or urbanicity strata. For example, the supply of center-based care for low-income families, or families living in rural areas may be equally scarce regardless of parental immigration status.

With regard to my second research question, I focused on estimating odds ratios of the immigrant concentration while holding other variables the same. I hypothesized that *community-level immigrant concentration decreases the likelihood of preschool enrollment among immigrant families*. This is based on the assumption that as the proportion of immigrants within a community increases so too does the availability of potential child care providers (unemployed), and this may serve as a constraint to preschool access especially when childcare cost is a burden to the family.

The spatial assimilation framework suggests that immigrant parents may pass on perceived opportunities or constraints to their children through their choice of settlement locations. On the structural level, the demographic and socio-economic composition of the community either attracts childcare services to operate or deter them from entering the community. Given the barriers in access to preschool common to immigrant families discussed earlier, I hypothesized that *the supply of childcare (having access to preschool or lacking thereof) may affect childcare choices differently by parental immigration status* (question 2).

CHAPTER 4: METHODOLOGY

Previous published empirical work on childcare choices has used either nationally representative data (Coley et al., 2014) or individual state data (Forry et al., 2014). While these studies provide a broad understanding of the factors affecting childcare choices at the family level, conceptually and methodologically, they have either overlooked the heterogeneity among childcare alternatives (Davis & Connelly, 2005) or failed to make a strong case about how the immigrant context interacts with childcare choices. In this study, I addressed these shortcomings by combining data from the Early Childhood Longitudinal Study-Kindergarten Class of 2010-11 (ECLS-K:2011), the Common Core of Data (CCD), the Early Childhood Learning and Knowledge Center (ECLKC), the Homeland Infrastructure Foundation-Level Data (HIFLD), and the U.S. Census Bureau. Doing so allows me to create a comprehensive data set linking the supply of childcare services, the four-year-old child, his/her family, the type of childcare used during the pre-K year, and community characteristics in which they live. With this combined data set, I used a conditional logit model to examine the effect of childcare supply on childcare choices made by immigrant and U.S.-born parents during the pre-K year.

This chapter is organized into five sections. In section 4.1, I introduced the multiple data sets to be used in this study. In section 4.2, I defined the term “community” used interchangeably with “proximity” or “local market” throughout this proposal, and explained how I reconciled the different geographic units used by the data sets and link them to the ECLS-K:2011 using Geographic Information System (GIS) software, ArcMap 10.5. In section 4.3, I described measures for the childcare choice model, and in section 4.4, I discussed the analytic plans for using the conditional logit model. I ended the chapter with a discussion of the study's limitations in section 4.5.

4.1 Data Sources

Children in my primary research data set, the ECLS-K:2011, entered kindergarten in the 2010-2011 school year. In order to study the supply conditions that predict their parents' childcare choice for the pre-K year, I use data on these children from the 2009-2010 school year, their pre-K year. Parents may have started their initial searches for childcare based on the available childcare options during the 2008-2009 school year, especially spring 2009, right before the enrollment in fall 2009. However, the choice sets from which parents could actually choose were those existing in the 2009-2010 school year. Therefore, I decide to use data from the 2009-2010 school year, the pre-K year, to measure different childcare alternatives available to each family. This applies to all data sets, as summarized in Table 4. 1, except for the American Community Survey from which I used the 2007-2011 estimates (discussed in detail in section 4.1.5). Table 4.1 provides an overview of the data sources, the supply of childcare each data source measure, the data collection year, and the geographic unit at which the data were collected.

Though these data sources allow me to create a unique, comprehensive data set to answer questions about the supply-side effects on immigrant parents' childcare choices, they are limited in some ways. Ideally, I would have location- and year-specific data, which would allow me to measure the number of care providers by childcare alternative within each family's proximity during the year before kindergarten. In other words, it would be ideal to have the addresses of all childcare providers for all types of care during the 2009-2010 school year. However, as shown in Table 4. 1 under the column "Geographic Unit", only a few data sources meet this criterion (e.g., the CCD and the ECLKC). Some, such as the HIFLD, only have location-specific information, while the other, such as the ZBP, only the year-specific information. In the section below, I discuss these differences in detail by describing the sampling method for each data set, the rationale to include it in this study, its shortcoming(s) and how I address them, when applicable. Details of the data set quality are included in Appendix A. Technical Report (Section A.2).

Table 4. 1 Data sources for supply of childcare

Data Source	Supply of Childcare Providers	Data Year	Geographic Unit
Early Childhood Longitudinal Study-Kindergarten: 2011 (ECLS-K:2011)	Parental care Relative care	2009-2010	n/a
Common Core of Data (CCD)	State pre-K	2009-2010	address
Early Childhood Learning and Knowledge Center (ECLKC)	Head Start	2009-2010	address
Homeland Infrastructure Foundation-Level Data (HIFLD)	Childcare centers	Various years	address
Zipcode Business Patterns (ZBP)	Family childcare homes	2009	Zip code

4.1.1 Early Childhood Longitudinal Study-Kindergarten: 2011 (ECLS-K:2011)

The ECLS-K:2011 is the most recent administration of the Early Childhood Longitudinal Study (ECLS) program from the National Center for Education Statistics (NCES). It followed a nationally representative sample of children who started kindergarten in the 2010-2011 school year through 5th grade. Similar to the previous ECLS-K study, the ECLS-K:2011 collected information about children’s experiences in many contexts and on a wide array of topics, including the characteristics of the child and the child’s family, education arrangements, and school and classroom environments (for more details, see Tourangeau et al., 2015). Approximately 18,000 kindergarteners in the 2010-2011 school year from about 970 schools, along with their parents, teachers, and school administrators, participated in this study. Data were collected through direct child assessment, parent interviews, teacher and school administrator questionnaires, and before- and after-school care provider questionnaires. I used the ECLS-K:2011 to measure the *supply* of parental care, *supply* of relative care, and control for the child, family, and school characteristics.

The ECLS-K:2011 used a three-stage complex survey sampling design. In the first stage, the U.S. was divided into 1714 primary sampling units (PSUs), from which 90 were sampled, including the 10 large PSUs. The remaining 80 PSUs were selected using stratified random sampling based on metropolitan area, population, geographic region, per capita income, and race/ethnicity composition of five-year-olds living in the PSUs. In the second stage, schools that educated children of kindergarten age (five-year-old children) were selected within the sampled PSUs, with probability of selection proportional to the size of kindergarten enrollment. This resulted in 720 public schools and 180 private schools. In the third stage, children enrolled in kindergarten from the selected schools were divided into two independent sampling strata, one including Asian, Native Hawaiian, and Pacific Islander students (APIs), and the other including all other students. Within each stratum, children were selected using equal probability systematic sampling. Within each school, API children were sampled from the API stratum at 2.5 times the rate of sampling used for non-API children in the non-API children stratum to ensure their adequate representation.

4.1.2 Common Core of Data (CCD)

The CCD, another program of the NCES, is the main data source to measure the *supply* of state pre-K programs at the address level during the 2009-2010 school year. The CCD annually collects data about all public schools, public school districts, and state education agencies in the U.S. It is the U.S. Department of Education’s primary database on public elementary and secondary education in the country. Each year, data requests are sent to each state education department through five sets of surveys, and the state education agencies compile CCD requested data into prescribed formats and transmit the information to NCES. The CCD, which consists mainly of administrative records, provides descriptive data on approximately 100,000 schools in three categories: general information on schools and school districts, such as name and address; aggregate information on students and staff, such as demographics; and fiscal data, such as revenues and current expenditures. From the CCD, I use the address information of all public schools that offered pre-K during the 2009-2010 school year. This allowed me to visualize the distribution of state pre-K programs within each family's proximity in the ECLS-K:2011 using GIS (see Figure 4 in section 4.2.2). The data are publicly available and downloaded from the NCES https://nces.ed.gov/ccd/elsi/ CCD website. There were 25,604 public schools in 47 states (excluding California, Michigan and Oregon) plus the District of Columbia that reported pre-kindergarten enrollment, ranging from 20 schools in Wyoming to 3737 schools in Texas. Table A.1 summarizes the number of schools with pre-kindergarten grade, the average enrollment per school, and the total pre-kindergarten enrollment at the state level.

However, the CCD data come with two major flaws. First, the CCD has severely limited data for California, Michigan and Oregon for the 2009-2010 school year. My email correspondence with the NCES staff member confirmed that California has not been able to report state pre-K enrollment because California's state pre-K program is administered by the Department of Health and Human Services rather the state education agency. Instead, pre-K data for CA in the CCD consisted only of counts of children receiving special education services. For

Michigan and Oregon, the CCD state pre-K data were what the state reported to the CCD[2]. Therefore, these three states are excluded from my final analyses.

The second flaw with the CCD data is the potential undercount due to program offerings in locations other than the public school systems. States vary in program venues—public schools, Head Start centers, childcare centers and community-based settings—through which the state-funded pre-K slots are provided. The CCD state pre-K data, however, include information on state pre-K provided in public schools only, which accounted for 62 percent of state pre-K enrollees in 2009-2010. Nearly 38% of state pre-K enrollees attended Head Start, childcare centers, or community-based settings, which are not included in the CCD data. Due to lack of data, I was not able to account for state-funded pre-K offerings through childcare centers. This has the potential of generating downward bias on the effect of state pre-K supply on childcare choices.

4.1.3 Early Childhood Learning and Knowledge Center (ECLKC)

The Early Childhood Learning and Knowledge Center, within the Administration for Children and Families (ACF) under the U.S. Department of Health and Human Services (DHHS), provides a comprehensive array of information on Head Start, ranging from grants and oversight, policy and regulation, and collaboration and partnerships, to data and reports. Similar to the CCD, the ECLKC data is used to measure the *supply* of Head Start for the 2009-2010 school year. I used two sets of administrative data it offers—the Head Start Center Locations Datasets (HSCLD) and the Program Information Report (PIR)—to measure the supply of Head Start in the 2009-2010 school year. The HSCLD[3] contained a list of all current Head Start

[2] Email correspondence with NCES staff is available upon request.
[3] The data were initially downloaded in excel format in April 2017. This has been transferred to an interactive map format on the website in June 2017.

centers whose directors have access to input their addresses into this online database (location-specific). The PIRs are annual mandatory surveys of all Head Start grantees, which collect detailed program-level information on the services, staff, children, and families served by Head Start and Early Head Start programs nationwide. In other words, the PIRs are year-specific data.

By hierarchy, each Head Start program may oversee several Head Start delegates. I use the 2009-2010 PIR to filter out Head Start delegates that did not exist in the 2009-2010 school year from the HSCLD in order to get a list of location- and year-specific Head Start centers for the 2009-2010 school year, in particular. One caveat with this strategy is that I may overcount Head Start locations under programs that have expanded since 2009-2010. In other words, these programs began to oversee additional locations that started operation after the 2009-2010 school year, but I won't be able to tell which centers came to existence after the 2009-2010 school year. This has the potential of generating upward bias on the effect of Head Start supply on childcare choices.

4.1.4 Homeland Infrastructure Foundation-Level Data (HIFLD)

The HIFLD are collected, processed and shared by the HIFLD subcommittee established in 2002 within the U.S. Department of Homeland Security. It is comprised of more than 270 national geospatial data sets across multiple levels of government under 24 public domains, ranging from agriculture, borders, and chemicals to public health, transportations, and water supply. Nested within the *Education* domain is the data set for *Day Care Centers*, which I used in this study to measure the *supply* of centers. The HIFLD contains the address (physical and in longitudes and latitudes), enrollment, and type (center-based, school-based, Head Start, religious facility) of all day care centers for all 50 states, District of Columbia and Puerto Rico. All the data were acquired from respective states departments or their open source websites.

Unlike the CCD and ECLKC data which are both year- and location-specific, the HIFLD day care center data are only location-specific. The current dataset is updated in different years with data in 25 states most recently updated in 2015. Table 4. 2 displays the years in which data were recently updated in each state. Three states have data updated in multiple years. Massachusetts has data mostly updated in 2009, with 2 observations in 2010. Maryland has data mostly updated in 2011 with one observation in 2010. New Mexico has data updated across 2010 (46 observations), 2011 (365 observations), and 2012 (329 observations).

Table 4. 2 HIFLD data currency by state

Year	States
2015	AK, AR, AZ, CA, CT, FL, GA, IA, ID, IN, KY, LA, MI, MO, MN, MS, MT, NC, NV, NY, OH, PA, SC, SD, and TX
2014	AR
2013	AK
2012	NM[1]
2011	HI, IL, KS, MD[2], NM, and WA
2010	AL, DC, DE, MA, MD, ND, NH, NM, OK, OR, TN, UT, VA, VT, WI, WV, and WY
2009	MA[3], ME, NE, and NJ

[1]NM: 2010, 2011, 2012.
[2]MD: mostly in 2011, 1 observation in 2010.
[3]MA: mostly in 2009, 2 observations in 2010.
Source: HIFLD

Despite not being year-specific, these day care center data contributed to this study in two major ways. First, it is, to my knowledge, the most comprehensive data set of all day care centers in the country. Next, the HIFLD allow one to exclude day care centers that enroll only infants and toddlers by center name, which the ZBP, described below, can not differentiate. However, since data from different states in the HIFLD were updated in different years, they do not provide accurately year-specific (2009-2010) data. Therefore, the CCD state pre-K data and the ECLKC Head Start data, both location-specific and year-specific, are preferred data sources to represent the supply of state pre-K and Head Start, respectively, even if state pre-K and Head Start locations are available in the HIFLD.

4.1.5 U.S. Census Bureau

4.1.5.1 Zip Code Business Patterns (ZBP)

The Zip Code Business Patterns (ZBP) is part of the County Business Patterns, an annual survey that collects economic data by industry at the U.S. Census Bureau. An establishment within each industry is classified by its physical location where some form of business activity is conducted, and the owner of the establishment reports administrative data. Published primarily according to the 2007 North American Industry Classification System (NAICS), the ZBP provides data on the number of businesses by employment size that are located within each zip code. Relevant to this study is the 2007 NAICS code 624410 for childcare services which is defined as "establishment primarily engaged in providing day care of infants or children." [4] According to the ZBP website on the childcare services industry, these childcare establishments cover a wide array of childcare services, ranging from informal babysitting services at the provider's home, family childcare homes, to formal day care centers, state pre-K, or Head Start centers that are not located within a public school. The employment size is grouped as 0-4 employees, 5-9 employees, 10-19 employees, with increasing increments to 500-1000 employees.

However, after checking with U.S. Census staff, I confirmed that there is no further breakdown as to what employment size corresponds to which type of informal or formal childcare services[5]. In other words, the ZBP does not identify childcare type. For this reason, even though the ZBP has the aggregated number of a wide array of childcare services by employment size and is year-specific, the CCD, the ECLKC, and the HIFLD are still the

[4] For the 2007 NAICS definition of 624410 Child Day Care Services, go to: https://www.census.gov/cgi-bin/sssd/naics/naicsrch?code=624410&search=2007%20NAICS%20Search

[5] Email correspondence with Census staff is available upon request.

preferred data sources for the provision of state pre-K, Head Start, and centers, respectively. The ZBP data, therefore, is used to measure of the *supply* of non-relative care, especially the number of family childcare (FCC) homes.

The next step is to determine which employment size range in the ZBP may correspond to the size of a FCC home. State child care licensing regulations and policies vary in the ratio and group size requirements for FCC homes. In general, FCC homes have fewer providers, and are allowed to serve fewer children than center-based childcare settings. For small FCC homes, there is typically only one provider in the home caring for a mixed-age group of children, and the common number of children allowed to be cared for by one provider ranges from four to six. For large FFC homes, the provider-child ratio can vary between 4:1 for children younger than 3 years and 10:1 for children age 3 and older, and the common number of children allowed to be cared for in state licensed large FFC homes ranges from seven to 12 children (NCCIC & NARA, 2010; Office of Child Care, 2011). Therefore, it makes sense to count childcare establishments with 0-4 employees in the ZBP as FCC homes, serving as the *supply* of FCC homes.

However, using the ZBP data means two additional compromises. Besides the fact that these data are not location-specific, it risks the issue of undercount of other informal non-relative providers, such as neighbors or friends who could also care for the child. Second, it may also risk the issue of overcounting FCC homes that provide afterschool care exclusively for school-aged children, rather than preschool-aged children. As mentioned earlier, the ZBP doesn’t differentiate between types of care or the age group of children cared for.

4.1.5.2 American Community Survey (ACS)

The American Community Survey (ACS), another data set from the U.S. Census Bureau, collects detailed information on the demographic, social, and housing characteristics across the country. It is administered every month to sampled households and produces estimates that describe the average characteristics of an area over a time period. Different from previously discussed data sources, the ACS data are used to account for the demand for childcare among children under age 5 as well as control for community characteristics, such as percent of foreign-born population, median household income, female labor force participation rate, and the composite poverty rate.

The ACS uses a complex two-phase process to sample Housing Unit (HU) addresses in each county (for more details, see U.S. Census Bureau, 2014). The first phase involves two stages. In the first stage, new addresses are systematically assigned to five existing sub-frames. One of the sub-frames is then identified to associate with the current year. This ensures that no HU address will be sampled more than once in any five-year period. In the second stage, HU addresses are systemically sampled from the selected first-stage sub-frame. HU addresses sampled during the first phase will receive a paper questionnaire without regard to legal status or citizenship of the household members and an automated Internet instrument in the mail. In the second phase, samples of unmailable addresses and non-responding addresses are sent to computer-assisted phone or personal interviews.

The ACS collects information differently based on area population. For areas with populations of 65,000+, data are collected during a single calendar year and saved as ACS 1-year estimates. For areas with populations between 20,000 and 65,000, data are collected over a three-year period and saved as ACS 3-year estimates. For areas with the smallest populations (i.e., less than 20,000), data are collected over a five-year period and saved as ACS 5-year estimates. Data collection for each population size happens every month, and is spread evenly across the entire period—one year, three years, or five years—respectively, as not to over-represent any particular month or year within the period (U.S. Census Bureau, 2009).

For this study, I use the 2007-2011 ACS 5-year estimates at the census tract level that describe the average characteristics over the 5-year period with data collected from January 1 of the beginning year to December 31 of the ending year. Using the ACS estimates and the 5-year estimates, in particular, has several advantages. The ACS estimates, in general, collect data over a period of time, rather than "point-in-time" estimates, such as those from the Decennial Census or the Current Population Survey. For a geographic area that may have experienced a major change or consistent changes, the ACS period estimates may capture the effect of the change in the population more accurately. The Decennial Census or the Current Population Survey, on the other hand, may produce significantly different data depending on when in the calendar year the measurement occurred.

With regard to choosing between the three estimates of different data collection lengths, although less current compared to the 1-year and 3-year estimates, the ACS 5-year estimates have two unique strengths. To begin with, the ACS 5-year estimates are based on the largest sample sizes and therefore are more reliable among the three ACS estimates. Next, and most importantly, the ACS 5-year estimates, in particular, cover smaller geographic units not available from the 1-year or 3-year estimates, for example, the census tract level that provides more accurate community context than the zip codes. The zip codes are a geographic boundary designed for the efficient delivery of mail, therefore, they are an imperfect unit for statistical analysis. A census tract, on the other hand, is a relatively permanent statistical subdivision of a county covering a contiguous area contained by visible and identifiable geographic features or legal boundaries. It is usually a smaller geographic area than a zip code polygon with a population between 1200 and 8000 people (see Figures 4.2 and 4.3 for the size comparison between zip codes and census tracts).

4.2 Measures

To examine the effects of childcare supply on family-level childcare choices, I include elements from the data sources, discussed above, to measure different aspects that I've identified through the literature review and conceptual frameworks. These include the supply of childcare (section 4.2.2), the demand for childcare (family-level demand and community-level demand) (section 4.2.3), the immigration context (section 4.2.4), and the community context (section 4.2.5). Table B.1 in Appendix B lists all variables for the study and data sources for which they were collected. All dollar values are converted to 2010 values, when applicable.

4.2.1 Childcare choice (outcome measure)

A family's childcare choice during the pre-K year is the outcome measure. In the ECLS-K:2011, parents were asked to identify the type of childcare their child received during the pre-K year. These childcare types can be categorized into six mutually exclusive options: parental care, relative care, non-relative care, center, state pre-K, and Head Start. The type of care used during the pre-K year is assigned the value of one while the other five unselected alternatives are assigned the value of zero. For children in the ECLS-K:2011 who had more than one care arrangements during the pre-K year, the value of one is assigned to (1) the type of care where the child spent the most time, (2) the formal care arrangement (center, state pre-K, or Head Start) if the child spent equal amount of time in multiple care arrangements, one of which being formal preschool (center-based care, state pre-K, or Head Start), or (3) the one randomly chosen when the child spent equal amount of time in two formal or informal arrangements.

Unlike the ECLS-K and ECLS-B that do not differentiate preschool beyond childcare centers and Head Start (Crosnoe et al., 2016; Gordon et al., 2012), the ELCS-K:2011 allows researchers to examine a third form of preschool, state pre-K. In the fall parent interview, parents were asked a series of questions that can help identify state pre-K participation: if the center their child attended during the year before kindergarten was "state funded," "located in a public school," or "located in the same school as kindergarten", common features associated with state pre-K programs.

4.2.2 Supply of childcare[6]

Measures of childcare supply come from the five data sources mentioned above: the HIFLD, the CCD, the ECLSK, the ZBP, and the ECLS-K:2011. Because data from these sources are collected at different geographic units, I created a physical area around the child's home zip code centroid, the physical center of the zip code polygon, called the *buffer*, to link the child in the ECLS-K:2011 to the various types of childcare. The goal of creating the buffer was that it sets the boundary within which I measured the number of care providers for each childcare alternative, as specified below. The area within the buffer was also referred to as the community. I described in more detail how the buffer was set up in section 4.3.

Supply of center-based care. The number of center-based day care centers available within each child's community was aggregated from the HIFLD. The HIFLD includes specific addresses for each childcare facility. Addresses included to account for the supply of center-based care applied to those that (1) enrolled four-year-olds (by excluding infant and toddler centers), and (2) were labeled as either center-based or religious facilities (by excluding school-

[6] I rescaled the number(s) of formal care arrangements to accommodate the small numbers of relative care, parental care, or FCC homes to avoid convergence issue.

based and Head Start programs). I then aggregated the number of childcare centers located within the buffer as the supply of center-based care.

Supply of state pre-K and Head Start. The numbers of state pre-K programs and Head Start centers are obtained from the CCD and ECLKC, respectively, for the 2009-2010 school year. Both data sets include addresses of program locations. Similar to the calculation of childcare centers, I used the aggregated numbers of these two programs within the buffer to measure the supply of state pre-K and Head Start locations, respectively. For state pre-K, in particular, I excluded those that meet this criterion, but are located in a bordering state because an eligible child can only enroll in the state program within his or her state of residency.

Supply of non-relative care. The number of childcare establishments with 0-4 employees (most likely FCC homes) from the ZBP was aggregated over all zip codes whose centroids fall within the buffer area. It accounts for the supply of non-relative care.

Supply of relative care. In the parent interview of the ECLS-K:2011 conducted in fall of the kindergarten year, one question asked if relatives lived with the focal child. If the answer was yes, the supply of relative care is assigned the value of 1, otherwise, the value of 0. Admittedly, this measurement is less than accurate. On the one hand, there was no additional information the relative(s). The relative(s) would only be considered available to care for the child if s/he was unemployed and capable to care for a child. On the other hand, it is impossible to know if there was a relative living nearby who could also be available to care for the child. Therefore, I could only rely on information from the ECLS-K:2011 to proximate the number of relatives available to care for the child, which may be lower or higher than the actual availability of relative care.

Parental care. In the parent interview, one question asked if the focal child in the ECLS-K:2011 was cared for by a parent exclusively during the year before kindergarten. If the parent answered yes, the number of parental care provider is assigned the value of 1 or the value of 0 if the family used non-parental care during the pre-K year, assuming parental care was not available during the pre-K year.

4.2.3 Demand for childcare

Child and family attributes. This array of family-level attributes has been discussed in the in Chapter 2 under *resources and needs* (section 2.2.1). Specifically, I included two sets of variables representing the child's development before the pre-K year and family characteristics, respectively. For the child, several variables can account for the child's prior abilities that are believed to draw responses from the parent who would attempt to choose the best care arrangement to meet the child's needs. These included the child's age, gender, race, and indicators for low-birth weight, preterm birth, breast feeding, special needs, twin/multiple birth, birth complication, first word spoken after 15 months old and first step taken after 15 months old.

For the family characteristics, measures included the family's socio-economic characteristics as well as family structure, such as maternal education, family income, family size, single-parent household, number of siblings, household food security, public assistance at child's birth, and mother's age at first birth, religion, and region. As discussed earlier, maternal employment and childcare decisions are considered jointly determined, making it inappropriate to control for maternal employment (Powell, 1997; Magnuson et al., 2007).

Market-level demand. In addition to the individual child and family characteristics that influence childcare choices, I included the number of children under age 5 as a demand variable at the community level. More children needing childcare may attract more childcare services to the area, thus expanding access for all needy families. Conversely, more children in need of childcare may also lead to long wait lists to enroll in existing childcare services, thus negatively affecting access to childcare services.

4.2.4 Immigration context

There is an array of variables collected in the ECLS-K:2011 to describe the parental and the child's immigration status. In addition to the key variable, *parental foreign-born status*, I also included the following variables to capture the family's immigration context—*child's citizenship status, parental age of migration to the U.S.*, and *years in the U.S. prior to first child birth.* Immigrant parents not only come from different countries and regions, but they also differ in the stage of their own development at the time of immigration and their socialization for parenthood since arriving in the U.S. The parental age of migration may have differential effects on children's social development and early cognitive development (Glick et al., 2009, 2012). Years in the U.S. prior to the first child's birth may also capture the social capital immigrant parents have accumulated when making the childcare choice for the pre-K year, though these measures may risk collinearity with socioeconomic status. In cases where both parents are immigrants, I average these measures between the two parents.

The ECLS-K:2011 also collected additional information regarding the *parent's English proficiency*, information that was not available in previous ECLS studies (Crosby & Mendez, 2016). In the fall parent interview, parents were asked to rate their abilities in reading, writing, speaking, and understanding English, where 1 indicated very well and 4 not so well. I reversed the scale so that a higher value indicates a higher level of proficiency. These reversed values across the reading, writing, speaking, and understanding domains are aggregated to create a composite English proficiency measure, ranging from 1 to 16.

4.2.5 Neighborhood context

The immigrant concentration and local socioeconomic conditions can also have great implications for the residents and the local supply of childcare. At the individual level, immigrant parents may have preference over the density of immigrants when making residential decisions. However, the level of immigrant concentration doesn't always correspond to the same level of socio-economic conditions. Therefore, I included other measures from the ACS 2007-2011 5-year estimates: *percentage of foreign-born population*, *tract median household income*, *female labor force participation*, and the *composed poverty rate*, and average them across census tracts within the buffer.

4.3 Data Merging Plan Using GIS

These data sets, representing the supply of each childcare alternative, the demand for childcare, and the neighborhood context, are collected at different geographic units by different federal agencies. In order to link them to the sample children in the ECLS-K:2011, I used ArcMap10.5 to add them as geographic layers to the smallest geographic unit available in the ECLS-K-2011, the zip code. In the following section, I discussed how I defined the community within which the supply of childcare alternatives are examined. I then described how I link the data collected at different geographic units to the zip codes in the ECLS-K:2011.

4.3.1 Defining the community

The community, a concept I have used interchangeably with the term "neighborhood", refers to the geographic proximity within each ECLS-K:2011 participant's home. The smallest geographic unit available in the ECLS-K:2011 is the child's home zip code. Therefore, I used the centroid of each child's home zip code as the center of the community. The literature offers a distance parameter (distance from the center) to define the community, but there may also be a need for a time parameter (time travelled from the center of the community). For this reason, I included three parameters to define the geographic community, as discussed below.

4.3.1.1 Distance parameters

Various studies measure the community using distance as the parameter. In the ECE literature, Coley and colleagues (2014; 2016) used 20 miles from the zip code centroid of each ECLS-K participant to define the community. They used this parameter to measure the availability of one particular childcare alternative, childcare centers. A Census Bureau report found out the national average commute distance between home and work was 18.8 miles (Mckenzie & Rapino, 2011). Assuming that parents search childcare services either near home or along their way to work, these two numbers seem to back each other well. However, this range of distance is debatable. This radius seems too large. I plugged in the supply of state pre-K and Head Start addresses in ArcMap10.5 within a 20-mile radius of an urban zip code to test. It turned out, not surprisingly, that urban residents have more publicly funded preschool options close to their unban residences, therefore, making it less convincing that they would drive 20 miles for childcare when they are many options much closer[7]. This rendered the 20-mile radius less appropriate in measuring the actual community of childcare providers for urban residents who have higher childcare service density in their immediate proximities (see Figure 4.1 for an example).

Findings from the National Survey of Early Care and Education yield shorter distances from home to the childcare provider (NSECE, 2016), providing new distance parameters for this study. On average, childcare centers for children age three to five are reportedly 3.9 miles away

[7] One may argue that state pre-K and Head Start programs can have waitlist, therefore, eligible children may not always get enrolled in the program close to home. However, given the fact that eligible children are often from low-income families, how these families could afford transportation or commute to a program location 20 miles away still makes the 20-mile radium less realistic.

from home. Therefore, I used 5 miles as the average commute distance from homes to childcare providers, or as the parameter for the community within which parents look for childcare services. In addition, this Survey also showed that the distance ranges from less than 1 miles to more than 8 miles. Given the discussion above about the consideration of commute distance and time, I also included a 10-mile parameter in my data analysis.

4.3.1.2 Time parameter

In addition to using the distance parameters, 5 miles and10 miles, I also included a time measure—25 minutes—to define the community. Depending on the urbanicity of the residential locations and the surrounding traffic patterns, the commute time may weigh in more than the commute distance in the childcare choice decision. The average commute time to work in the U.S. was 25 minutes in 2009 (Mckenzie & Rapino, 2011), the pre-K year for the sampled children in the ECLS-K:2011. Based on the assumption that parents would drive as far as they would have to do for work, this time parameter may more precisely account for the condense traffic condition in urban areas than the distance parameters. I ruan the same set of analyses using the distance and time parameters, and compared differences in the estimated coefficients on childcare supply among the three parameters.

Admittedly, using time as the parameter is not the perfect solution to the issues associated with the distance parameter. On the one hand, the actual commute time varies individually depending on the means of transportation and the time of departure (McKenzie & Rapino, 2011), both of which are unobserved from the ECLS-K:2011. On the other hand, both the distance and the time parameters may cover a much larger area than the actual childcare supply market within which parents would search for childcare services. This is because if the previous assumption of distance to work corresponding to that travelled to childcare provider holds true, then a subsequent assumption would be that parents would only search areas along the way to work from home, instead of the whole area centered on the focal child's home zip code centroid. Nevertheless, the distance and time parameters would have great potential in measuring supply of childcare services if future ECLS programs could collect data related to either commute distance or time from home to childcare provider.

4.3.2 Merging data sets using ArcMap10.5

Enclosed within the buffer is a confined area which I refer to as the community. The buffer is centered at the zip code centroid of each focal child from the ECLS-K:2011 with three parameters to define the area of the community: 5 miles, 10 miles (the distance parameters) and 25 minutes (the time parameter). As shown in Table 4.1, data to be used in this study are collected at different geographic units: the CCD, Head Start, and HIFLD have the addresses of all state pre-K (school-based), Head Start, and childcare center locations; the ZBP collects data at the zip code level. The number of children under age 5 and the neighborhood characteristics from the ACS 5-year estimates are at the census tract level. Using ArcMap10.5, I merged addresses from the CCD, Head Start, and HIFLD, zip codes from the ZBP, and census tracts from the ACS to each zip code centroid of sampled children in the ECLS-K:2011, illustrated below. In this merging process, I either aggregated the number of each childcare alternative or averaged the neighborhood characteristics over respective geographic units that fall within the buffer area of each focal child's zip code centroid. For zip code (ZBP data) and tract (ACS data) polygons that were located along the buffer border, I only included those whose zip code or tract centroids fall within the buffer area. Details on the specific tools used in ArcMap10.5 which set the parameters can be found in Appendix A, section A.3.

4.4 Analytic Plan

In this study, I used a conditional logit model (CLM) to predict how community-level childcare supply affects family-level childcare choices during the pre-K year. The conditional logit model, also referred to as the McFadden's qualitative choice behavior model (McFadden, 1973), is a maximum likelihood estimation model. It has been used to answer an array of consumer choice problems such as choice of residential location, labor force participation, choice of automobiles or travel destination (Blaise, 2005; Davies, Greenwood, & Li, 2001; Friedman, 1981; Haan, 2006; Hoffman & Duncan, 1988; McFadden, 1978), and choice of college attended (Long, 2004; Radner & Miller, 1970).

The CLM allows researchers to methodologically account for attributes of the supply that the commonly used multinomial logit models (MNL) can't do. First and foremost, the conditional logit model considers attributes of the alternatives themselves in addition to those of the individuals in predicting the probabilities of choosing each childcare alternative. Therefore, it is a more appropriate model when the childcare choice is conceptualized as a function of the supply of available childcare alternatives. Second, the CLM could produce estimates that are more practical and policy relevant. It allows me to predict how changes in the number of one choice alternative would affect the probability of choosing this or other alternatives. For example, I can estimate changes in the probability of enrolling in Head Start if a state pre-K location opens in the community.

Following a random utility model, the CLM assumes that a sampled individual I (i = 1, … , I) faces a choice amongst J childcare alternatives (J=6) in each of the T choice situation. In the supply effect model, t equals 1 because parents made childcare choice only once for the pre-K year, so I omit subscript *t* in the following discussion. The probability of a family *i* choosing childcare choice *j* can be summarized in Equation (1) (McFadden, 1974):

$$P_{ij}(J = 6) = \frac{e^{x_{ij}\beta'}}{1 + \sum_{k=2}^{J} e^{x_{ik}\beta'}} \tag{1}$$

In the context of this study, P_{ij} represents the conditional choice probability of each individual family *i* selecting childcare alternative *j* for the pre-K year from six mutually exclusive childcare alternatives (*J* = 6): *center*, *state pre-K*, *Head Start*, *relative*, *non-relative*, and *parental care*. x_{ij} is a vector of an observable attribute specific to the childcare alternative *j* (the number of childcare alternative available to each family), and attributes specific to each individual family *i* (i.e., child and family characteristics, neighborhood characteristics, and childcare care demand of the local market). The standard error is clustered at the zip code level. In general, scaling matters in maximum likelihood estimation models, including conditional logit model, so I rescaled independent variables, when necessary, so that it doesn't affect convergence.

Data analyses were ran using *STATA 14.1*. *STATA* requires that the data be stored in long form, which means the observations are at the child-choice level. The *Stata* code for conditional logit model is provided below.

```
asclogit choice number, casevars($child $family $neighborhood
demand i.state) case(CHILDID) alternatives(childcare) or
vce(cluster zip)
```

where `asclogit` is the *STATA* command for the CLM. `choice` is the dependent variable with a value of 1 for the chosen childcare alternative during the pre-K year and a value of 0 for the remaining five unselected childcare alternatives. Closely following the dependent variable is the alternative-specific variable `number`, representing the number of each childcare alternative available to each focal child within the local market, which varies across the six childcare alternatives per child and across individual children. This is one of the key independent variables for this study. `$child $family $neighborhood` are vectors of individual-specific variables describing the individual child (prior abilities), family, and neighborhood attributes, specified by `casevars($child $family $community demand)` where `demand` is the average number of children under age 5 across all selected census tracts. The decision maker is denoted by `case(CHILDID)`, and the six mutually exclusive childcare alternatives are denoted by `alternatives(childcare)`. Standard errors are clustered at the zip code level by the `vce(cluster zip)` option.

I specified *STATA* to report odds ratios by the `or` option. Coefficients in logit models only have directional meaning as to whether the individual is either more or less likely to choose each alternative. I instead estimated odd ratios which indicate how much one was more or less likely to choose each childcare alternative given a set of fixed values of all predictors. An odds ratio greater than 1 indicates a positive effect while less than one indicates a negative effect. I also estimated predicated probabilities. Marginal effects of CLM analyses are reported in Appendix C.

4.5 Limitations

While this study was the first to use a comprehensive set of data sources to estimate the supply effect on childcare choices, and among the first few to use the conditional logit model in educational research, it has several shortcomings. As discussed throughout in section 4.1, the data sources used to measure the supply of each childcare alternative are not perfect. Even the

ECLS-K:2011 data have a major flaw. Information on the family characteristics in the ECLS-K:2011 was collected in kindergarten fall (2010) or spring (2011) semesters and, therefore, may not reflect the actual attributes prior to making the childcare decision for the pre-K year in 2009. This possible disparity has been previously addressed in the literature by adding both the family attributes collected in the kindergarten year and the family's public assistance receipt at the time of child's birth (Magnuson et al., 2007), which I adopt in my analyses.

In addition, it is worth to point out that results from this study are contingent upon on the sizes of the buffer, determined by the three parameters used, 5 miles, 10 miles, or 25 minutes. Even though anecdotes indicate that parents tend to choose childcare providers along the way to work or close to either work or home, in the ECLS-K:2011, neither the commute time or distance to work was available, nor do I know which ECLS-K:2011 families chose care providers close to home or to work. Had such information been available, I would have had a more accurate measurement of the buffer area. I also acknowledged, again, that my definition of the community (i.e., 5 miles, 10 miles, or 25 minutes from a zip code centroid) was broader than a traditional neighborhood, and was geographic rather than social (Jencks & Mayer, 1990). It is also a broader area in the sense that parents would probably only look in the direction between home and work, rather than searching the whole area for childcare services.

Next, due to data limitation, this study only focusesd on the effect of one aspect of the childcare supply, *quantity*. It is nearly impossible to include attributes of all available alternatives in the analysis, because often the case, researchers only have data on the attributes of the chosen alternative. Similarly, two other important supply factors at the alternative level—quality and cost—may also affect families' childcare choices. These two indicators can either be used as the key independent variables or to be set as having random parameters assuming parents may have different preference for program quality and cost. As states continue to build their QRIS systems, future research may consider incorporating quality measures into this model.

Last but not least, while the child sample of interest is children of immigrant parents, where immigrant parents can be either documented or undocumented by status, it is not possible for me to tell if the study sample from the ECLS-K:2011 included undocumented immigrant parents, or the number of them, if any. Therefore, this study could not particularly address the supply of children options for undocumented immigrants.

CHAPTER 5: FINDINGS

In answering questions about access to preschool, in particular, the effects of childcare supply, parental immigration status, and community-level foreign-born population on childcare choices, descriptive and conditional logit model analyses were conducted for the three buffer sizes around each child's home zip code centroid, as described in Chapter 4. Children of immigrant parents during the pre-K year had more access to centers, Head Start, and state pre-K although they were enrolled in centers at lower rates than their counterparts of U.S.-born parents. Access, in this context, means the number of a given childcare option available to the child within each buffer, as defined by either the distance or commute time from the child's home zip code centroid (5 miles, 10 miles, and 25 minutes). The number of childcare care centers did not significantly affect the likelihood of enrolling in center, while having at least one immigrant parent negatively impacted the odds of center participation. In addition, the supply of childcare options, especially that of childcare centers, have differential effects on center enrollment by parental immigration status, and, even having more access to childcare centers couldn't offset the negative effect associated with having at least one immigrant parent, as measured by the predicted probabilities. Detailed of these findings, which confirmed two out of three of my hypotheses, are described in the following sections.

5.1 Description of the Child, Family, Childcare Choice and Supply, and Community

Tables 5.1 and 5.2 present summary statistics from t-test, respectively, to portray children, family, childcare choices, and community characteristics by parental immigration status and childcare options. With regards to child and family characteristics, the overall comparison about families and childcare choice patterns between children of immigrant and U.S.-born parents were consistent with prior research findings (columns 1 and 2 under “Overall”). However, there was more within-variation among children of immigrants across the six childcare options than between subgroups of children by parental immigration status who were enrolled in the same type of childcare. The same was almost true for the contextual factors (i.e., community characteristics), except for the percent of foreign-born population, as described in detail below.

5.1.1 Child, family, and childcare choices

Overall child and family characteristics

Table 5.1 displays child and family characteristics of the overall sample and subgroups of children who used the same childcare option during the year prior to kindergarten arrayed by parental immigration status. As summarized in the first two columns of Table 5.1, the two groups of children (children of immigrant parents and children of U.S. born parents) differed across racial and socioeconomic characteristics, characteristics that often predict childcare choices in previous studies.

First, the race/ethnicity composition of the two groups were significantly different. Among all children of U.S.-born parents, nearly three quarters were White (72 percent), while the largest race/ethnicity subgroup among children of immigrant parents were Hispanic, comprising 55 percent of all children of immigrant parents in the study sample.

Looking at family income, reported poverty, and public assistance receipt indices (i.e., WIC benefits), children of immigrant parents experienced higher rates of financial hardship than children of U.S.-born parents. Over one-third of them lived in households within an annual income of $25,000 or less (38 percent), while the percentage for children of U.S.-born parents was 23. At the same time, 37 percent of households with at least one immigrant parent reported living in poverty, while the rate for households with U.S.-born parents was 19, or approximately half the rate. In addition, households with at least one immigrant parent had higher rates of receiving WIC benefits. Fifty-one percent of them reported receiving WIC during pregnancy, and 57 percent reported that the child received WIC, while the rates for households with U.S.-born parents were 39 and 42, respectively.

Other family characteristics, such as highest parental education level and single-parent household status, show expected yet interesting patterns. Similar to prior research findings, children of immigrant parents were more likely to have parents with lower educational attainment. Among them, one out of four had parents who did not graduate from high schools, and this rate was four times higher than that of their counterparts with U.S.-born parents (6 percent). In addition, children of immigrant parents were less likely to have parents who graduated from high school (45 percent vs. 56 percent) or had a bachelor's degree (18 percent vs. 26 percent). Interestingly, however, 12 percent of children from immigrant households had parent(s) who had a master's degree or beyond, which was 0.5 percentage higher than that of children of U.S.-born parents. Also consistent with prior findings is that children of immigrant parents, overall, are less likely than children of U.S.-born parents to live in a single-parent household (16 percent vs. 28 percent).

Finally, there are significant, yet expected, differences with regards to home language and urbanicity. While over half of children of immigrant parents were reported to speak a language other than English as their primary language at home (52 percent), less than one percent of their counterparts with U.S.-born parents did. Children of immigrant parents were also more likely to live in cities (41 percent) and suburbs (39 percent), whereas children of U.S.-born parents are more likely to live in suburbs (35 percent) and rural areas (28 percent).

Childcare choice patterns

With regards to childcare choices during the year prior to kindergarten, one expects that childcare choice patterns would differ by parental immigration status, given differences in family characteristics described above. Indeed, the data for this study are consistent with this expectation and with previous findings. Looking at the first row of Table 5.1, 21 percent of children of immigrants were enrolled in childcare centers during the year prior to kindergarten. This is about 10 percentage points lower than the center participation rate among children of U.S.-born parents (32 percent). On the other hand, children of immigrant parents had slightly higher participation rates in Head Start and state pre-K, respectively—ranging from less than one to nearly three percentage points—than children of U.S.-born parents. In addition, while nearly one of three children with immigrant parents were cared for by a parent (30 percent), the rate was less than one in five for children of U.S.-born parents (18 percent).

Differences in child and family characteristics by childcare choice

The remainder of Table 5.1 compares child and family characteristics between subgroups of children by parental immigration status who enrolled in the same type of childcare option during the year prior to kindergarten. As shown in the two columns under "Center," children who were enrolled in childcare centers demonstrated different racial/ethnic and income characteristics compared to children who used the other five childcare options, regardless of parental immigration status. First, almost all subgroups across the six childcare options followed similar race/ethnicity composition patterns where the predominant racial group for the specific childcare option was Hispanic among children of immigrant parents, and White among children of U.S.-born parents. The only exception was observed among children of immigrant parents who were enrolled in center where Hispanic had much lower participation rate (10 percent), compared to 36 percent of White and 27 percent of Asian.

Second, children who were enrolled in childcare centers also had, on average, better educated parents and older mothers, and lived in families with higher annual incomes. Specifically, these children were more likely to have parents who graduated from college or received an advanced degree (66 percent among children of immigrant parents and 59 percent among children of U.S.-born parents, respectively). More than half of children enrolled in childcare centers lived in families with an annual income of $75000 and above (61 percent among children of immigrant parents and 58 percent among children of U.S.-born parents, respectively, who attended childcare centers). On the other hand, Head Start participants were more likely to come from families with an annual income of $25000 or less (56 percent and 50 percent, respectively).

Looking at public assistance receipt, the two subgroups of center participants, children of immigrant and U.S.-born parents, also had the lowest rates of receiving WIC or living in poverty when compared to their counterparts who were not enrolled in center care. Mothers of these children who were enrolled in centers also were older when they gave birth to the first child, at age 28 and 27, respectively, among children of immigrant parents and children of U.S.-born parents. Mothers of Head Start enrollees were the youngest when they gave birth to their first child, at age 22 and 22, respectively.

Moreover, children of immigrant parents enrolled in center care were less likely to speak a language other than English as their primary home language (36 percent), compared to children of immigrant parents enrolled in other care options. This was 15 percentage lower than the average, and nearly half of the rate among children of immigrant parents enrolled in Head Start

(62 percent of children of immigrants enrolled in Head Start spoke a language other than English as their primary home language).

5.1.2 Childcare supply

Next, I ran t-tests on the overall sample and subgroups of children who used the same childcare option during the year prior to kindergarten arrayed by parental immigration status, in order to answer my first research question: *How does the supply of childcare options available for children of immigrants in the United States compare with supply for children of U.S.-born parents*. The results are summarized in Table 5.2. Similar to Table 5.1, the first row of Table 5.2 indicates the overall sample and subgroups of children using each childcare option during the year prior to kindergarten. Three panels are included, each representing a buffer size: 5 miles, 25 minutes, and 10 miles. Specifying the buffer size three ways allowed me to explore the possibility of finding a more appropriate buffer size to study childcare choices, which seems inconclusive in the existing literature. As will be shown in detail below, the patterns were in general consistent for the two groups of children (children of immigrant parents and children of U.S.-born parents) across childcare choice and buffer size. Variations in those patterns are also noted.

Table 5. 1 Characteristics of children and their families by childcare choice and parental immigration status

	Overall			Center			Head Start			State pre-K			Non-relative care			Relative care			Parental care		
	Immigrant parents	U.S.-born parents		Immigrant parents	U.S.-born parents		Immigrant parents	U.S.-born parents		Immigrant parents	U.S.-born parents		Immigrant parents	U.S.-born parents		Immigrant parents	U.S.-born parents		Immigrant parents	U.S.-born parents	
Childcare choice	n/a	n/a		21.45	32.12	**	8.50	8.33	**	23.47	20.59	**	4.18	8.60	**	12.62	12.63		29.78	17.73	**
Immigrant measures																					
Child is U.S. citizen	94.54	99.73	**	95.73	99.84	**	96.42	99.52	**	96.22	99.73	**	96.03	99.60	**	96.67	99.88	**	94.22	99.65	**
Child's race																					
White	21.74	71.98	**	35.63	80.08	**	8.12	49.37	**	13.21	64.00	**	30.97	87.00	**	13.81	67.11	**	15.26	68.11	**
Black	6.00	13.57	**	4.95	7.72	**	6.93	29.58	**	3.81	17.02	**	3.45	3.95	**	4.36	14.38	**	4.44	12.55	**
Hispanic	55.06	9.32	**	19.92	7.25	**	76.87	13.93	**	70.00	11.83	**	50.46	6.71	**	62.29	13.71	**	65.93	13.54	**
Asian	11.24	0.20	**	26.86	0.41	**	5.49	0.46	**	9.28	0.18	**	10.27	0.53	**	12.71	0.13	**	9.64	0.20	**
Other and multi-racial	5.96	4.93	**	12.64	4.55	**	2.59	6.66	**	3.70	6.98	**	4.85	1.81	**	6.82	4.67	**	4.73	5.61	**
Family characteristics																					
Income																					
$25000 or less	37.56	22.57	**	9.50	8.64		56.37	50.24		43.71	26.86	**	25.85	7.56	**	33.71	27.20		49.20	31.64	**
$25001 - $50000	23.43	20.79	**	13.45	14.41		23.37	23.34		29.27	25.26	**	16.30	14.47	**	25.14	24.45		25.38	25.43	**
$50001 - $75000	12.42	18.94	**	15.79	18.82		10.09	11.30		8.95	18.62	**	23.90	28.09	**	16.72	20.10		11.13	17.73	**
$75001 and more	26.59	37.70	**	61.26	58.13		10.17	15.12		18.07	29.26	**	33.96	49.87	**	24.43	28.25		14.28	25.21	**
Highest parental educational level																					
less than high school	25.00	5.84	**	5.62	1.21	**	28.56	10.11	**	27.85	7.09	**	15.17	1.38	**	26.79	8.25	**	39.76	10.97	**
high school	44.50	56.48	**	28.22	40.13	**	54.64	74.96	**	50.73	61.56	**	46.94	53.07	**	50.00	65.11	**	43.11	63.98	**
Bachelor's degree	18.26	25.97	**	36.44	39.05	**	10.77	10.18	**	13.38	22.64	**	21.33	27.19	**	15.83	17.65	**	11.88	19.87	**
Advanced degree	12.24	11.72	**	29.72	19.60	**	6.04	4.76	**	8.05	8.71	**	16.56	18.37	**	7.38	9.00	**	5.26	5.18	**
Single-parent household	16.16	27.50	**	7.57	17.21	**	24.54	51.76	**	14.53	31.36	**	17.21	15.10		27.25	39.95	**	13.80	25.95	**
Family size (n)	4.81	4.47	**	4.34	4.30		5.11	4.41	**	4.77	4.49	**	4.43	4.51		5.05	4.47	**	5.03	4.79	
Home language other than English	51.92	0.91	**	32.01	0.11	**	61.48	2.06	**	58.22	0.82	**	36.44	0.18	**	54.23	1.71	**	68.65	1.86	**
Number of siblings (n)	1.55	1.48		1.28	1.34		1.62	1.45		1.57	1.51		1.32	1.51		1.40	1.40		1.82	1.73	
Poverty	36.98	19.49	**	8.86	6.85	*	55.79	43.18	*	43.18	24.13	*	23.41	5.36	*	32.42	23.00		49.77	28.61	*
Household food insecurity																					
low food insecurity	82.96	89.76	**	93.16	94.22		78.63	84.25		82.75	89.02	*	86.39	91.84	*	79.64	86.83	*	78.30	85.99	*
medium food insecurity	13.77	7.92	**	5.88	4.56		17.50	11.42		13.69	8.79	*	12.05	6.26	*	15.06	10.25	*	18.78	10.71	*
high food insecurity	3.27	2.32	**	0.96	1.22		3.88	4.34		3.56	2.20	*	1.55	1.90	*	5.30	2.92	*	2.92	3.30	*
Public assistance WIC																					
Mom received WIC pregnant	51.01	38.63	**	16.63	18.50		70.41	69.75		65.15	47.77	**	40.63	21.88	*	53.47	48.86		62.15	47.63	
Child received WIC	56.53	42.58	**	18.37	21.25		77.69	75.69		71.44	53.47	**	43.68	25.47	*	56.58	51.10	*	68.48	51.51	*
Food stamp	5.54	5.98		1.20	3.45	*	7.45	8.36		6.64	7.41		5.90	6.55		6.85	8.69		4.93	6.08	
Religious	46.38	60.61	**	43.93	62.19	*	45.24	56.88	*	42.42	59.90	*	44.57	64.88	*	46.84	54.32	*	43.35	57.58	*
Mother's age at first child birth (yrs)	24.38	24.55		28.21	26.97	**	22.06	21.84		23.77	23.46		23.88	25.78		23.50	23.29		23.32	23.09	
Mother was married at child birth	71.53	70.48		90.39	82.69	*	57.62	44.54	*	69.28	64.82		72.24	83.13		65.19	63.50		67.31	66.01	
Region																					
Midwest	13.25	25.80	*	17.01	25.17		11.02	25.95		11.62	27.81	*	19.51	51.15	**	11.37	26.90	*	8.18	19.46	
Northeast	19.40	16.88	*	23.65	20.47		14.41	14.61		10.74	12.03	*	4.18	10.85	**	13.71	14.06	*	10.69	11.86	
South	47.87	42.16	*	25.14	34.42		29.88	44.08		42.32	46.37	*	26.66	14.13	**	28.63	39.06	*	41.12	42.09	
West	19.47	15.16	*	34.20	19.94		44.69	15.35		35.31	13.80	*	49.66	23.87	**	46.29	19.97	*	40.01	26.59	
Urbanicity																					
City	41.00	22.23	**	40.32	26.18	**	55.18	28.13	**	44.95	22.33	**	53.56	14.00	**	48.06	22.41	**	51.80	25.26	**
Suburb	39.24	34.90	**	47.57	42.10	**	30.88	27.67	**	37.24	31.12	**	21.34	31.55	**	37.10	36.12	**	29.17	33.23	**
Town	5.68	14.59	**	2.95	10.28	**	3.75	14.83	**	4.70	15.96	**	13.75	23.40	**	5.30	13.41	**	5.42	12.22	**
Rural	14.08	28.28	**	9.15	21.44	**	10.20	29.37	**	13.12	30.58	**	11.35	31.05	**	9.54	28.06	**	13.61	29.29	**
Child characteristics																					
Age one year before K (months)	53.66	54.67	**	53.56	54.54	**	54.16	54.52		53.86	54.84	*	53.95	55.11		53.80	54.49		53.34	54.72	**
Girl	47.11	48.84		40.32	26.18		55.18	28.13		44.95	22.33		53.56	14.00		48.06	22.41		51.80	25.26	
Low-birth weight	9.22	8.42		47.57	42.10		30.88	27.67		37.24	31.12		21.34	31.55		37.10	36.12	*	29.17	33.23	
Preterm birth	17.62	21.46	**	2.95	10.28		3.75	14.83		4.70	15.96	*	13.75	23.40		5.30	13.41		5.42	12.22	
Breast fed	80.27	68.41	**	9.15	21.44	*	10.20	29.37	*	13.12	30.58	*	11.35	31.05		9.54	28.06	*	13.61	29.29	*
Speical needs	2.27	3.82	*	48.24	49.23		50.41	46.79	*	47.12	46.43		40.03	49.74		53.23	50.16		46.75	49.44	*

Twin/triplet	0.12	0.19		7.01	7.18		8.41	10.92		7.74	8.43		8.58	6.57		15.82	8.59		10.31	9.00	
Birth complication	11.62	14.85	*	18.36	20.10	*	19.63	23.08		15.94	22.88		17.73	20.12		22.85	21.46		16.10	19.57	*
Prior endowments																					
first word spoken after 15 mos	29.87	20.99	*	87.29	78.48	*	81.56	57.21		82.99	65.65	*	87.36	78.12		78.20	61.25	**	77.72	65.61	**
first step taken after 15 mos	8.14	7.08		1.23	1.49		0.00	6.69		4.15	6.48		0.00	3.15		3.41	3.16		1.56	3.78	
N	1407	5699		340	1905		116	467		319	1116		50	490		182	726		400	995	

** Statistical significance at the .01 level.
* Statistical significance at the .05 level.
Notes:
Numbers are percentages unless otherwise noted.
Column headers indicate the childcare arrangement selected during the year prior to kindergarten entry.
Monetary amounts are in 2010 dollars.

More access to childcare options among children of immigrants

Contrary to my first hypothesis that immigrant families had less access to preschool (i.e., childcare centers, Head Start, and/or state pre-K programs), the data suggest that children of immigrant parents lived in communities that had more childcare centers, Head Start, and state pre-K during 2009-2010. In the 5-mile model, the average number of centers in communities children of immigrants lived was 5.36, compared to 2.57 for children of U.S.-born parents. The average numbers of childcare centers in the 25-minute model are 14.69 and 7.81, and 22.8 and 11.21 in the 10-mile model. Access to Head Start programs followed the same patterns. In the 5-mile model, the average number of Head Start locations available for children of immigrant parents was 0.71, compared to 0.43 among children of U.S.-born parents. In the 25-minute model, the comparison was 2.02 versus 13, and in the 10-mile model, 2.26 versus 1.2. With regards to access to state pre-K, the average numbers of state pre-K programs available for children of immigrant parents and children of U.S.-born parents were 2.27 versus 1.06 in the 5-mile model, 7.18 versus 3.7 in the 25-mile model, and 6.81 versus 3.12 in the 10-mile model, respectively.

Not only was this pattern observed across the three buffer sizes, as shown in the first two columns under “Overall” in Table 5.2, it was also true between the two subgroups of children who chose the same childcare option during 2009-2010. Regardless of which childcare option the child used, children of immigrants had access to more children centers, Head Start, and state pre-K than their counterparts with U.S.-born parents.

Disparity between access to and use of childcare centers

With a particular interest in childcare centers, participation in which is reportedly associated with better school readiness skills, I examined the number of centers available to children in each subgroup (by childcare choice and parental immigration status). The data showed some disparities between access to childcare centers and the actual use of centers. For example, children who were enrolled in Head Start had access to the highest number of childcare centers. This was observed across the three buffer sizes, and for both children of immigrant and U.S.-born parents. The average numbers of centers available for Head Start children were 6.25 and 4.68, respectively, among children of immigrant parents and children of U.S.-born parents in the 5-mile model, 16.37 and 10.49 in the 25-minute model, and 28.54 and 13.86 in the 10-mile model. This was even more evident in the 10-mile model (the bottom panel in Table 5.2) where the numbers of centers for children who were enrolled in center care were slightly below the averages (22.80 versus 22.55 for children of immigrant parents and 11.21 versus 11.07 for children of U.S.-born parents). Together, these disparities between access to and use of childcare centers seem to suggest that, regardless of the buffer size, access to childcare centers may not guarantee enrollment.

Varying magnitudes of change in access to childcare options by buffer size

Table 5.2 also shows that the number of childcare options available to families increased as the buffer size changed, a pattern one would expect to see. However, the magnitude of changes in access to different childcare options differed. I reported these numbers by buffer size following this order as suggested by the data: 5 miles, 25 minutes, and 10 miles. Overall, across the three buffer sizes, the number of childcare centers increased significantly as the buffer size increased from 5 miles to 10 miles. For example, among children of immigrant parents, the average number of childcare centers within 5 miles, 25 minutes, and 10 miles were 5.36, 14.69, and 22.8, respectively. Among children of U.S.-born parents, the numbers were 2.57, 7.81, and 11.21, respectively. However, the supply of the other childcare options—Head Start, state pre-K, and FCC homes—did not follow the same pattern. The numbers of these childcare options increased significantly when the buffer size changed from 5 miles to 25 minutes, but remained relatively stable, if not smaller, between the 25-minute and 10-mile models.

5.1.3 Contextual factors

In short, children of immigrants lived in families that differ systematically in terms of racial/ethnic, income, and educational attainment from their counterparts with U.S.-born parents, attended centers at lower rates, but had access to a larger supply of centers, Head Start, state pre-K across the three buffer sizes. I now turn to other contextual factors which may help to explain the disparity in center participation rates between the two groups of children (children of immigrant parents and children of U.S.-born parents).

The demand for childcare as measured by the percent of children age 5 within a community, as well as the community characteristics are summarized in Table 5.2. Some patterns emerged with regards to the demand for childcare across the three buffer sizes. Regardless of parental immigration status, subgroups of children who enrolled in centers lived in communities with lower than average percentages of children age 5 and under, while subgroups of children who used parental care lived in communities with the highest percentages of children age 5 and under. On the other hand, children of immigrant parents who enrolled in Head Start and state pre-K, in particular, lived in communities with higher than average demand. The same was observed among children of U.S.-born parents who used non-relative care.

The second half of each panel in Table 5.2 labeled as “Community characteristics” summarizes the community characteristics per buffer size. Overall, compared to peers with U.S.-born parents, children of immigrant parents lived in communities with a larger foreign-born population, slightly higher concentrations of poverty, lower female workforce participation rates, and somewhat higher median household income. These community characteristics did not vary much across the three buffer sizes. However, there was variation in community characteristics between children of immigrant parents and children of U.S.-born parents who used the same childcare option.

To begin with, a variable of interest for this study, the percent of foreign-born population, the overall average percentages of foreign-born population across the three buffer sizes range from 16 (10-mile buffer) to 17 (5-mile buffer) among children of immigrant parents. These percentages were nearly twice of those for children of U.S.-born parents across the three buffers (8.1 percent for the 5-mile model, 8.64 for the 25-minute model, and 8.51 for the 10-mile model) Looking at children of immigrant parents, in particular, those who were enrolled in centers lived in community with slightly more foreign-born residents than the average among all children of immigrants in this sample, while those enrolled in Head Start and state pre-K lived in communities with less foreign-born residents than average among all children of immigrants in this sample. On the other hand, children of U.S.-born parents who enrolled in state pre-K lived in communities with lower percentages of foreign-born residents, so did subgroups of children who used non-relative care.

Not surprisingly, community-level poverty rates followed similar patterns to family income across the six childcare options. The overall average poverty rates for both children of immigrant and U.S.-born parents were about 13 or 14 percent across three buffer sizes, however, subgroups of children who enrolled in centers lived in communities with lower poverty rates, while subgroups of children who enrolled in Head Start and state pre-K or used parental care lived in communities with higher poverty rates. Female labor force participation rates were about 22 percent on average, with 1 or 2 percentage points of variability across the three buffer sizes.

Among children of immigrant parents, those enrolled in centers lived in communities with the highest female labor force participation (23.04 percent for 5-mile model, 23.1 for 25-minute model, and 23.04 for 10-mile model); the same was true among children of U.S.-born parents who used non-relative care (23.09 percent for 5-mile model, 23.2 for 25-minute model, and 22.99 for 10-mile model). Finally, the community median household incomes, on average, ranged from over $57,000 to slightly over $60,000 across the three buffer sizes. Variation existed across subgroups of children under the six childcare options. Children of immigrant parents enrolled in center lived in communities with the highest median household incomes across all subgroups ($69,762.82 for 5-mile model, $66,074.27 for 25-minute model, and $66,967.78 for 10-mile model), whereas children of U.S.-born parents enrolled in Head Start lived in communities with the lowest household median incomes ($49,963.5 for 5-mile model, $52,229.39 for 25-minute model, and $51,775.99 for 10-mile model).

In sum, children of immigrant parents and children of U.S. born parents not only differed across racial and socioeconomic characteristics, characteristics that often predict childcare choices in previous studies, but also lived in communities characterized by differing economic development and demographic composition. Given variation in family-level and community-level characteristics, it was not surprising that children of immigrant parents and U.S.-born parents exhibited different childcare choice patterns during the year prior to kindergarten entry. Specifically, the data suggest that having more access to childcare centers, participation in which is reportedly associated with better school readiness skills, did not necessarily lead to enrollment in childcare centers among children of immigrant parents. In addition, with regards to child, family, and community characteristics (except for the percent of foreign-born population), I found less within-variation between children of immigrant parents and children of U.S.-born

Table 5. 2 Descriptive summary of supply of and demand for childcare and community characteristics by childcare choice, parental immigration status, and buffer size.

	Overall			Center			Head Start			State pre-K			Non-relative care			Relative care			Parental care		
	Immigrant parents	U.S.-born parents		Immigrant parents	U.S.-born parents		Immigrant parents	U.S.-born parents		Immigrant parents	U.S.-born parents		Immigrant parents	U.S.-born parents		Immigrant parents	U.S.-born parents		Immigrant parents	U.S.-born parents	
5-mile buffer																					
Number of care option																					
Center	5.36	2.57	**	6.10	2.39	**	6.25	4.68		6.10	2.60	**	4.36	1.36	**	5.70	2.23	**	3.85	2.76	*
Head Start	0.71	0.43	**	0.61	0.34	**	0.79	0.81		0.86	0.46	**	0.80	0.29	**	0.71	0.45	**	0.65	0.44	**
State pre-K	2.27	1.06	**	1.77	0.98	**	2.32	1.32	**	2.65	1.16	**	2.77	0.72	**	2.42	1.02	**	2.26	1.17	**
FCC homes	4.31	2.94	**	3.97	2.69	**	4.69	4.00		4.63	3.06	**	5.36	2.43	**	4.77	2.71	**	3.92	3.22	*
Demand for childcare																					
% children age 5 and under	6.73	6.41	**	6.15	6.30	*	6.84	6.38	**	7.00	6.43	**	6.72	6.29	**	6.73	6.49	*	6.99	6.60	**
Community characteristics																					
% foreign-born	17.04	8.10	**	14.87	8.56	**	18.95	7.01	**	18.49	8.34	**	14.36	6.55	**	17.48	7.79	**	17.31	8.42	**
% composed poverty rate	14.82	13.41	**	11.00	11.68	*	17.04	16.35		16.52	14.30	**	14.13	11.38	**	13.75	14.52		16.65	14.51	**
% female labor force participation	21.97	22.25	**	23.04	22.82		21.22	21.61		21.23	21.84	**	22.71	23.09		22.37	21.90	*	21.59	21.72	
median household income (2011 dollar)	59889.19	58294.73	**	69762.82	64092.18	**	54864.23	49963.50	**	56083.78	55690.23		59111.38	59457.23		60485.78	55229.63	**	55814.45	55690.50	
25-minute buffer																					
Number of care option																					
Center	14.69	7.81	**	17.62	8.31	**	16.37	10.49	**	15.31	7.69	**	11.43	4.67	**	15.81	7.32	**	11.13	7.62	**
Head Start	2.02	1.30	**	1.77	1.18	**	2.38	1.75	*	2.43	1.36	**	1.93	1.02	**	1.89	1.42	**	1.88	1.28	**
State pre-K	7.18	3.70	**	5.75	3.66	**	7.09	3.64	**	8.74	3.87	**	7.65	2.81	**	7.20	3.74	**	7.10	4.01	**
FCC homes	10.23	6.96	**	9.85	6.81	**	9.75	7.83	*	11.41	7.05	**	11.71	6.24	**	11.42	6.71	**	9.01	7.26	**
Demand for childcare																					
% children age 5 and under	6.69	6.45	**	6.32	6.39		6.71	6.39	**	6.87	6.41	**	6.75	6.38	**	6.56	6.50		6.92	6.62	**
Community characteristics																					
% foreign-born	16.39	8.64	**	14.82	9.23	**	18.08	7.51	**	17.99	8.96	**	13.69	6.92	**	16.16	8.19	**	16.41	8.87	**
% composed poverty rate	14.75	13.91	**	12.31	12.84	*	16.11	15.66		16.30	14.44	**	13.31	12.11	*	13.35	14.78	**	16.01	14.77	**
% female labor force participation	22.19	22.45	**	23.10	22.90		21.65	21.99		21.58	22.06	**	22.94	23.20		22.64	22.23	*	21.77	22.07	*
median household income	60369.45	57550.71	**	66074.27	61599.99	**	57265.89	52229.39	**	57293.72	55676.64		62184.74	58269.41	*	62344.59	55396.75	**	57747.70	55615.28	**
10-mile buffer																					
Number of care option																					
Center	22.80	11.21	**	22.55	11.07	**	28.54	13.86	**	26.54	11.55	**	18.20	7.72	**	22.20	10.13	**	19.23	12.38	**
Head Start	2.26	1.20	**	2.03	1.08	**	3.18	1.72	**	2.83	1.28	**	2.14	0.89	**	2.17	1.27	**	1.79	1.20	**

State pre-K	6.81	3.12	**	5.71	3.02	**	7.69	3.53	**	8.16	3.25	**	7.28	2.18	**	7.07	3.13	**	6.23	3.41	**
Family childcare homes	11.18	6.60	**	10.29	6.11	**	12.66	8.17	**	12.77	7.05	**	12.55	6.00	**	12.49	6.21	**	9.52	6.89	**
Demand for childcare																					
% children age 5 and under	6.62	6.37	**	6.18	6.28	*	6.76	6.33	**	6.83	6.36	**	6.61	6.30	**	6.55	6.43		6.82	6.57	**
Community characteristics																					
% foreign-born	16.33	8.51	**	14.53	8.98	**	18.17	7.42	**	17.88	8.65	**	13.92	7.13	**	16.08	8.13	**	16.52	8.93	**
% composed poverty rate	14.75	13.59	**	11.78	12.27		16.84	15.65		16.43	14.21	**	13.58	11.90	**	13.51	14.54	*	16.05	14.62	**
% female labor force participation	22.13	22.24		23.04	22.78	*	21.52	21.76		21.40	21.79	**	22.90	22.99		22.57	22.00	**	21.81	21.74	
median household income	60399.68	57726.76	**	66967.78	62511.84	**	56261.15	51775.99	**	57107.19	55341.03	*	61554.74	58334.44		61944.60	55219.78	**	57795.42	55564.13	**

** Statistical significance at the .01 level.

* Statistical significance at the .05 level.

Note:

Column headers indicate the childcare arrangement selected during the year prior to kindergarten entry.

Monetary amounts are in 2010 dollars.

parents who chose the same childcare option than among children of immigrant parents across the six childcare options. In other words, children and families that chose the same childcare options were somewhat more similar, regardless of parental immigration status, than subgroups of children with the same parental immigration status but who chose different childcare options.

5.2 Determinants of Childcare Choice

To further examine how the childcare supply, having at least one immigrant parent, and select community characteristics affect childcare choices, as measured by the type of childcare option the family chose during the year prior to kindergarten, I conducted conditional logit model analyses for all three buffer sizes, respectively, where parental care was set to be the base alternative. Odds ratios and predicted probabilities are reported below. Overall, parental immigration status had a negative impact on the likelihood of enrolling in childcare centers. The concentration of foreign-born residents within a community had small but significant negative effects on the probability of enrolling a child in a state pre-K program. The effect of supply of childcare centers had a small but significant negative impact on enrolling in centers among sampled children only for the 25-mile model. Effects of other contextual factors are also described below; their magnitudes and significance varied by childcare option and buffer size.

5.2.1 Differences in childcare choices as explained by parental immigration status and foreign-born population concentration in the community

Table 5.3 displays estimates from the conditional logit model. For each buffer size, the model estimated how the supply of childcare options, parental immigration status and select community characteristics affected the probability that a family would choose to use a given childcare option conditional on using any childcare options. As mentioned previously, the standard errors were clustered at the family zip code level. Odds ratios are reported with z-statistics (included in the parentheses in the table).

The interpretation of odds ratios is slightly different for the alternative-specific variable, the number of childcare options (which varied across the six childcare alternatives per child and across individual children), than for the individual-specific variables, such as parental immigration status and community contextual attributes. For the number of childcare options, the odds ratios can be interpreted as an increase in the number of childcare options by one for a given childcare option will increase or decrease the odds of choosing that childcare option by a certain percentage. For individual-specific variables, the odds ratios can be interpreted as an increase by one unit in the individual-specific variable will increase or decrease the odds of selecting this alternative versus selecting the base alternative. In running conditional logit models across the three buffer sizes, parental care is set to be the base alternative. Therefore, the estimated odds ratios could inform whether a unit of increase in these key variables of interest would increase the odds of choosing childcare centers versus using parental care. In the following sections where results from conditional logit model analyses were reported, I focused on those related to three particular formal care types: childcare centers, state pre-K, and Head Start, for the reason that participation in these programs have reportedly positive effects in preparing children ready for school.

Effects of key variables of interest

As expected *having at least one immigrant parent* negatively impacted the likelihood of a child being enrolled in a childcare center. The impact was quite consistent in magnitude across the three buffer sizes. In the 5-mile model, having at least one immigrant parent would decrease the probability of choosing childcare center versus using parental care by 37.1 percent, all else held equal based on the observed characteristics. In the 25-minute model, it decreased the probability by 37.7 percent, and in the 10-mile model, by 36.9 percent. The effects were statistically significant at the 0.05 level across the three buffer sizes. In the 25-minute model, in particular, having at least one immigrant parent also decreases the probability of choosing state pre-K versus using parental care by 21.7 percent, and the effect was statically significant at the 0.1 level.

The *concentration of foreign-born population* within a community had small but significant negative effects on the probability of enrolling a child in a state pre-K program. Across the three buffer sizes, a 10-percentage point increase in the concentration of foreign-born residents in a community negatively affected the probability of choosing state pre-K versus using parental care by less than 0.5 percent—0.3 percent in the 5-mile and 25-minute models, and 0.4 percent in the 10-mile model. In the 25-minute model, in particular, a 10-percentage point increase in the concentration of foreign-born population would decrease the probability of choosing a childcare center versus using parental care by 1.2 percent. This partially aligns with one of my hypotheses that community-level immigrant concentration will decrease the likelihood of preschool enrollment, although the effect was only significant for state pre-K enrollment, not for center or Head Start participations.

The fact that children of immigrant parents had a greater supply of childcare centers, Head Start, state pre-K programs and FCC than children of U.S. born parents, as described in Section 5.1 above, may explain why the alternative-specific variable, the *number of childcare options* (supply of childcare), does not have a large or significant impact on childcare choices. Except in the 25-minute model, the number of childcare options was not found to be an important factor in determining childcare choices. In the 25-minute model, having one additional care provider for a given childcare option increased the odds of using that care option by 0.1%, holding all else constant. This effect is statistically significant but quite small. In the 5-mile and 10-mile models, its effects were not statistically significant.

Effects of other contextual factors

Not surprisingly, the *demand for childcare* had a small but statistically significant effect on childcare choices, but not for all childcare options. In the 5-mile model, the odds of enrolling in Head Start versus using parental care decreased by 1.4 percent when the percent of children age 5 and under increased by 10 percent. There was a 2-percentage decrease in the likelihood in the 25-minute model, and 1.9 percent decrease in likelihood in the 10-mile model. These effects were quite consistent across the three buffer sizes. In the 10-mile model only, the demand for childcare also had a small but negative impact on enrolling in a childcare center versus using parental care. A 10-percentage increase would decrease the probability of enrolling in a childcare center by 1.2 percent.

Other contextual factors also showed some significant effects. First, *female labor force participation rates* had a small but negative impact on Head Start enrollment across the three buffer sizes. For each 10-percentage point increase in the community female labor force participation rate, the likelihood of enrolling in Head Start decreased by 0.7 percent in the 5-mile model, by 1 percent in the 25-minute model, and by 0.9 percent in the 10-mile model. The community affluence, on the other hand, had a small but positive impact on center participation for the 25-minute and 10-mile models. A 1000-dollar increase in the *community median household income* would increase the likelihood of using childcare centers by 2.9 percent in the 25-minute model and 1.3 percent in the 10-mile model. Similarly, the *child's citizenship status* had a much larger and significant impact on enrolling in childcare centers across all three buffer

Table 5. 3 Odds ratios of select variables of interest: Conditional logit models

Select variables of interest	Number of childcare options	Center	Head Start	State pre-K	Non-relative care	Relative care
5-mile	1.001					
	(-1.37)					
Immigrant measures						
At least one immigrant parent		0.629 **	1.003	0.800	0.681 *	0.876
		(-3.35)	(-0.02)	(-1.59)	(-1.72)	(-0.82)
Child is citizen		1.868 **	1.300	2.003 **	1.457	2.121 *
		(-2.06)	(-0.61)	(-2.12)	(-0.66)	(-1.90)
Demand for childcare						
% children age 5 and under		0.995	0.986 **	1.002	0.989	1.004
		(-0.98)	(-2.21)	(-0.39)	(-1.38)	(-0.69)
Community characteristics						
% foreign-born		0.999	1.000	0.997 **	0.999	0.999
		(-0.76)	(-0.2)	(-4.32)	(-1.06)	(-1.15)
% composed poverty rate		1.000	1.000	1.002	0.997	0.999
		(-0.08)	(-0.24)	(-1.24)	(-1.41)	(-0.50)
% femail laborforce participation		1.000	0.993 *	1.001	1.002	0.998
		(-0.05)	(-1.82)	(-0.40)	(-0.50)	(-0.62)
median household income (per $1000)		1.009	0.989	1.002	0.991	0.992
		(-1.43)	(-1.25)	(-0.37)	(-1.01)	(-1.16)
25-minute	1.001**					
	(-2.89)					
Immigrant measures						
At least one immigrant parent		0.623 **	0.987	0.783 *	0.699	0.875
		(-3.42)	(-0.07)	(-1.73)	(-1.61)	(-0.83)
Child is citizen		1.788 *	1.294	1.925 **	1.461	2.084 *
		(-1.91)	(0.59)	(2.00)	(0.67)	(1.85)
Demand for childcare						
% children age 5 and under		0.988	0.980 **	0.989	0.992	0.994
		(-1.64)	(-2.05)	(-1.58)	(-0.73)	(-0.69)
Community characteristics						
		**		**	*	
% foreign-born		0.998	1.001	0.997	0.997 *	0.999
		(-1.98)	(0.60)	(-4.09)	(-1.98)	(-1.51)
% composed poverty rate		1.004 **	1.001	1.004 **	0.998	1.002
		(1.96)	(0.42)	(2.17)	(-0.52)	(0.99)
% femail laborforce participation		1.003	0.990 **	1.000	1.005	1.000
		(0.79)	(-2.06)	(-0.12)	(0.81)	(-0.11)
median household income (per $1000)		1.029 **	1.002	1.016 *	1.003	1.005
		(3.49)	(0.20)	(1.86)	(0.25)	(0.53)
10-mile	1.000					
	(1.14)					
Immigrant measures						
At least one immigrant parent		0.631 **	0.993	0.796	0.686 *	0.878
		(-3.32)	(-0.03)	(-1.62)	(-1.70)	(-0.81)
Child is citizen		1.826 **	1.327	1.994 **	1.487	2.102 *
		(-1.99)	(-0.65)	(-2.10)	(-0.70)	(-1.88)
Demand for childcare						
% children age 5 and under		0.988 *	0.981 **	0.997	0.985	1.002
		(-1.89)	(-2.28)	(-0.45)	(-1.52)	(-0.32)
Community characteristics						
% foreign-born		0.999	1.000	0.996 **	0.999	0.998 *
		(-1.24)	(-0.28)	(-4.43)	(-0.80)	(-1.82)
% composed poverty rate		1.001	1.001	1.003	0.998	1.001
		(-0.76)	(-0.50)	(-1.34)	(-0.81)	(-0.35)
% femail laborforce participation		1.005	0.991 *	0.999	1.002	1.002
		(-1.47)	(-1.87)	(-0.19)	(-0.37)	(-0.50)

median household income (per $1000)	1.013 *	0.994	1.005	0.993	0.994
	(-1.71)	(-0.54)	(-0.60)	(-0.65)	(-0.61)

** Statistical significance at the .05 level
* Statistical significance at the .1 level
Note:
Z-statistics are reported in the parentheses to denote statistical significance. Effects are interpreted as the multiple by which the probability favoring choosing childcare option j is multiplied with a one-unit increase in that variable.
Monetary amounts are in 2010 dollars.

sizes. A child who was a U.S.-citizen was 86.8 percent more likely to enroll in a childcare center versus being cared for by a parent in the 5-mile model, 78.8 percent more likely in the 25-minute model, and 82.6 percent more likely in a 10-mile model than a child who was an immigrant in this study sample. This larger effect associated with being a citizen child versus an immigrant child may be due to the fact that then sampled children were disproportionately U.S. citizens.

5.2.2 Does childcare supply affect choices differently based on parental immigration status?

To test if the supply of childcare affects childcare choices differently by parental immigration status, my second research question, I estimated predicated probabilities at certain data values in Table 5.4. As with general linear models, one can change the value of predictors to produce predictions, which can show changes in the probability of choosing a given childcare option at specific values of the same predictor, holding all else at their means. This allowed me to examine whether the same change in the supply of centers would affect the probability of choosing center care for children of immigrant and U.S.-born parents similarly.

Column 2 in Table 5.4 shows the predicted probabilities of choosing the four childcare arrangement for the entire study sample holding all other variables at their means: 0.44 for enrolling in center, compared with 0.053 for Head Start, 0.265 for state pre-K, and 0.104 for FCC homes, in the 5-mile model. The probabilities of choosing center care decreased slightly as the buffer size increases to 25 minutes and 10 miles, as did the probabilities of choosing FCC homes. However, the probabilities of using state pre-K increased by about 2 percentage as the buffer size increased to 25 minutes and 10 miles.

Columns 3 and 7 of Table 5.4 display predicted probabilities under two extreme conditions regarding parental immigration status. Assuming all study children had U.S.-born parents, the probabilities that they would enroll in a childcare center are 0.454 for the 5-mile model, 0.419 for the 25-minute model, and 0.421 for the 10-mile model (column 3). When all study children had immigrant parents (column 7), the probabilities of enrolling in a childcare center decreased by about 7 percentage points across the three buffer sizes to 0.382, 0.347 and 0.356, respectively, indicating that having at least one immigrant parent negatively affected the likelihood of enrolling in a childcare center.

Next, I examined if the supply of childcare affects choices differently by parental immigration status, with a particular focus on different levels of the supply of childcare centers. In other words, I estimated predicted probabilities under three specific supply conditions of childcare centers. Columns 4 through 6 in Table 5.4 display predicted probabilities of choosing a given childcare option, assuming all study children had *U.S.-born parents*. Each of these columns represents a unique supply condition where the number of centers increased by 1, 3, and 5 from the average number of centers in each model, holding all other predictors at their means. In columns 8 through 10, I replicated the same supply conditions, assuming all study children had *immigrant parents*. As expected, increasing the number of centers did increase the likelihood of enrolling in a childcare center across the three buffer sizes.

Nevertheless, the increase in number of centers still did not offset the negative impact associated with having immigrant parents. For example, looking at center enrollments in column 10, the predicted probability of enrolling in a childcare center in the 5-mile model when all children had immigrant parents is 0.453, which is 0.1 percentage lower than that for when all children had U.S.-born parents (column 3), even when children of immigrants had three more centers in their communities. This discrepancy was widened as the buffer size increased. In the 25-minute model, the predicted probability of enrolling in a childcare center for children of

Table 5. 4 Predicted probabilities by parental immigration status, number of centers, and buffer size

Childcare option	**at means[1]** (default)	**all U.S.-born parents[2]**				**all immigrant parents[3]**			
		at means	mean+1[4]	mean+3[5]	mean+5[6]	at means	mean+1[4]	mean+3[5]	mean+5[6]
1	2	3	4	5	6	7	8	9	10
				5-mile					
Center	0.440	0.454	0.477	0.502	0.526	0.382	0.404	0.428	0.453
Head Start	0.053	0.049	0.047	0.045	0.043	0.068	0.065	0.063	0.060
State pre-K	0.265	0.259	0.248	0.237	0.225	0.283	0.273	0.262	0.251
FCC	0.104	0.105	0.101	0.096	0.091	0.098	0.095	0.091	0.087
				25-minute					
Center	0.405	0.419	0.432	0.446	0.460	0.347	0.359	0.372	0.386
Head Start	0.056	0.053	0.052	0.050	0.049	0.071	0.070	0.069	0.067
State pre-K	0.282	0.278	0.272	0.265	0.259	0.296	0.291	0.285	0.279
FCC	0.103	0.104	0.102	0.099	0.097	0.099	0.097	0.095	0.093
				10-mile					
Center	0.409	0.421	0.424	0.428	0.432	0.356	0.359	0.362	0.366
Head Start	0.050	0.047	0.047	0.047	0.047	0.064	0.063	0.063	0.063
State pre-K	0.302	0.297	0.295	0.294	0.292	0.318	0.316	0.315	0.313
FCC	0.099	0.100	0.100	0.099	0.098	0.093	0.092	0.092	0.091

[1] Mean values for the numbers of childcare options are the default values:

5-mile model: center=3.125, Head Start=.48437, state pre-K=1.298 and FCC=.21544.

25-minute model: center= 9.1722, Head Start= 1.4407, state pre-K= 4.387 and FCC= .75521

10-mile model: center=13.509, Head Start=1.4095, state pre-K=3.8472 and FCC=0.73425

Mean=0.198 (p_immigrant)

[2] This is assuming all children had U.S.-born parents.

[3] This is assuming all children had immigrant parents.

[4] This will add a value between 1 and 2 to the mean of the number of centers while the numbers of other childcare options remain the same. The number of center is set to:

5 for the 5-mile model,

11 for the 25-minute model, and

15 for the 10-mile model.

[5] This will add a value between 3 and 4 to the mean of the number of centers while the numbers of other childcare options remain the same. The number of center is set to:

7 for the 5-mile model,

13 for the 25-minute model, and

17 for the 10-mile model.

[6] This will add a value between 5 and 6 to the mean of the number of centers while the numbers of other childcare options remain the same. The number of center is set to:

9 for the 5-mile model,

15 for the 25-minute model, and

19 for the 10-mile model.

immigrant parents was 0.386, which was still 3.3 percentages lower than that of children of U.S.-born parents (column 3), even though they had access to three more childcare centers. The discrepancy is 5.5 percentages in the 10-mile model. This may indicate that immigrant parents were less likely to use centers located further from home, reflecting the lack of transportation or information of care options. Findings from Table 5.4 align with my second hypothesis that the supply of childcare (having access to preschool) affects childcare choices differently by parental immigration status.

5.3 Which Buffer Size is Preferred?

So far, I have described descriptive and inferential results for the three buffer sizes in the first two sections above. Next, to test which buffer size may predict childcare choices more appropriately, I plotted residuals from models using the three buffer sizes. The residual plot is a helpful tool to examine how the model fits the data, in this case, how the three buffer sizes fit the data (more details on residuals are provided in Appendix A, Section 4.2).

Figure 5.1 below displays residual plots for the three buffer sizes. The plots suggest that the 25-minute model fits the data slightly better than the other two models, though the evidence is less than strong. Measures of fitness across the three measures are also compared. Comparisons did not yield significant differences across the three buffer sizes. For more details on the fitness measures, please refer to Appendix A, Section A.4.

The lines in each plot represent four childcare options: center, Head Start, state pre-K, and non-relative (FCC homes). The top portion of each plot, the area where the value on the y-axis is above 0, shows trends in residuals as the number of childcare options increases among cases where the specific care option was chosen during the year prior to kindergarten, whereas the bottom portion shows trends in residuals as the number of children options increases when the specific care option was not the care option chosen. Ideally, in a perfectly fitted model, one would expect the residual curve of a specific childcare option in both portions to be around 0. I did not include parental or relative care in the plots because the number of these two care options was arbitrarily assigned the value of 1 when it was the chosen care option during the year prior to kindergarten, and 0 otherwise. The trends and directions of these residuals, as described below, suggest that the 25-minute model is more appropriate.

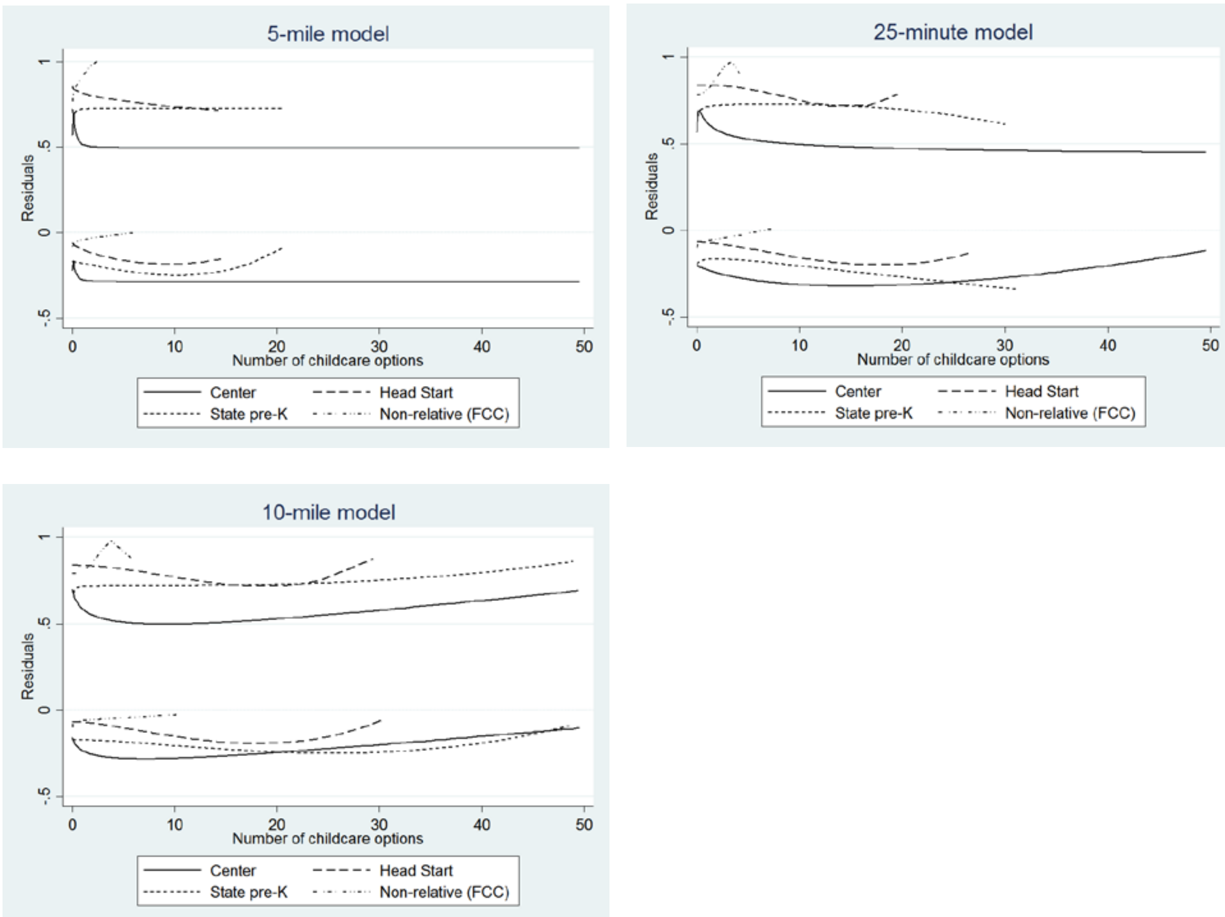
Across the three residual plots by buffer size, some patterns emerge in Figure 5.1. First, the models predicted the probabilities of choosing center care better than those of choosing Head Start, state pre-K, or FCC homes, as shown by the solid line in the top portion of each plot. Compared to the other three lines representing the residuals for Head Start, state pre-K, and FCC, the residuals of center use, the solid lines, were the closest to 0.

Second, the models may under-predict the use of center, Head Start and state pre-K when the supply of these options in a community was low. The residual curves of these three childcare options showed a downward trend to varying degrees as the supply increased, suggesting that the models began to fit the data better.

Third, the residual curves of center, Head Start and state pre-K displayed an opposite direction overall, compared to those of the FCC homes, until the supply passed a certain point in the 25-minute and 10-mile models. This may indicate that the models were less sensitive when the supply was low and the sensitivity level varied by childcare option.

Finally, looking at the 25-minute model specifically (as this is the only model where the residuals of center use eventually decreased to pass a 0.5 threshold), the center use residuals decreased as the number of centers increased and in the same direction, which aligned with the patterns observed in the predicted probability table above.

Figure 5. 1 Residual plots by buffer size.



CHAPTER 6: DISCUSSION

In this study, I combined data from the Early Childhood Longitudinal Study Kindergarten Class 2011, the Common Core of Data, the Early Childhood Learning and Knowledge Center Head Start data, the Homeland Infrastructure Foundation-Level Data, and the U.S. Census Bureau to examine whether and how childcare supply affects childcare choices between immigrant and U.S.-born parents. By using a conditional logit model, this study reveals that children of immigrant parents had more access to centers, Head Start programs, and state pre-K although they were enrolled in centers at lower rates than peers with U.S.-born parents. The number of childcare care centers, in particular, did not significantly affect the likelihood of enrolling in center care, while having at least one immigrant parent negatively impacted the odds of center participation. However, the supply of childcare, especially that of childcare centers, had differential effects on center enrollment by parental immigration status, and, even having more access to childcare centers could not offset the negative effect associated with parental immigration status, as measured by the predicted probabilities.

6.1 Implications from Findings

6.1.1 Beyond supply

It seems counterintuitive that having more access to center care does not directly translate to higher probabilities of using childcare centers for children of immigrant parents. This may indicate a couple things. On the one hand, it could be something other than supply that affects the choice, such as cost, or enrollment capacity, for example. When the cost is high, the affordability becomes an issue even if access is not a problem. Unlike the number of centers, the enrollment capacity is a more detailed measure of access because larger numbers of childcare centers do not necessarily mean more center slots, if each childcare center offers limited slots. Having these measures would portray a more comprehensive picture of the supply condition.

On the other hand, there may be more variations involved in the decision-making process. For example, parents may rely on different sets of determinants when considering different childcare options. It is possible that convenience factors, such as distance, are more important for parents who decide to use non-relative care, than those who would be willing to travel a little further for center care. Either way, it points to the need for more alternative-specific data (supply), which may be feasible for future survey studies to collect.

6.1.2 Explaining differential effects across the three preschool types

The fact that parental immigration status only negatively affects the odds of using childcare centers, rather Head Start or state pre-K enrollments, may indicate that certain aspect(s) of childcare centers are more sensitive to parental immigration status than are those of Head Start or state pre-K programs. Again, the first aspect could be cost, as described above. Childcare centers normally charge a fee unless parents are eligible for and receive childcare subsidies to offset the financial burden. Head Start and state pre-K are publicly-funded programs, therefore, do not require parents to pay or pay little. Since children of immigrant parents are more likely to experience poverty than peers with U.S.-born parents, immigrant parents may not be able to afford enrolling their children in childcare centers. Another possibility is program location or distance from home. Head Start and state pre-K, compared to childcare centers, could be more community-based, therefore, located close to where immigrant families live. For example, descriptive statistics reveal that unlike the number of childcare centers, the numbers of Head Start and state pre-K programs did not change significantly when the buffer size changed from

25 minutes to 10 miles, indicating these is little supply beyond a certain distance point. Finally, one could assume that Head Start and state pre-K programs had better outreach activities into immigrant communities so that immigrant parents knew they had such options for childcare.

6.2 Data Infrastructure

This study relies on several data sets, four of which are administrative data and the rest survey data to create a new comprehensive data by spatially joining them to the ECLS-K:2011. Research using matched survey sample data and administrative data, such as this current study, can benefit from both worlds—the rich demographic details available from survey data combined with detailed programmatic data from the administrative records. However, the merging of these data sets raised issues that need to be addressed in order to provide more accurate and useful data for early childhood education studies. Recommendations on how the overall data infrastructure can be improved are discussed below by data type.

6.2.1 Improving survey data

The recommendations listed below relate to data from the two surveys used in this study: the ECLS-K:2011 and the ACS. These recommendations address specific data issues evident in this study and are aimed to improve data quality for future studies exploring the topic of childcare choices.

Collecting data on more supply-specific attributes

In future ECLS-K studies, such as the ECLS-K:2023 which may include a preschool-year data collection round, the study design may consider including a few questions that ask either parents or childcare providers for more information, such as distance to and cost of childcare options, and/or enrollment capacity. Collecting such information would provide valuable data for studies focusing on supply while not dramatically increase the burden on the respondents.

Verifying zip codes before data release

The spatial joins applied in this study reveal a surprising finding that there are zip codes in the ECLS-K:2011 that can not be found in GIS zip codes files. In other words, there were non-existent zip codes. It will negatively affect the sample size if a case could not be joined using geographic information. In future survey data collection and cleaning processes, it would be a good practice to verify if all zip codes indeed exist.

Reducing nonresponse

Nonresponse could adversely affect the final estimates when item nonresponse is high as this will introduce bias, especially if the actual characteristics of the people who did not respond to a question differ from those who did. The ACS estimation methodology includes imputations for item nonresponse, intended to reduce the potential for item nonresponse bias. An advantage associated with survey data, such as the ACS, in reacting to nonresponse is that the data collection agency may be able to conduct some type of nonresponse analysis to find out differences between respondents and non-respondents. This may, in turn, allow them to take differential approaches in study recruitment and retaining respondents. In addition, each data collection could provide a better data user manual where the data collection agency describes who the non-respondents are so the data users can conduct non-response analysis and find out if nonresponseness introduces bias.

6.2.2. Improving administrative data

Improving the quality of administrative data would require more systematic changes. The recommendations listed below are ideal as I acknowledge that they are not equally possible or feasible to implement. The first three recommendations are low hanging fruits that can be achieved within the data collection agency. The last two recommendations would require collaboration and communication with stakeholders external to the data collection agency.

Reducing nonresponse rate and missing data

As with survey data, nonresponse is also a threat to administrative data. When data merging is involved, not having certain data in the administrative data further reduces the sample size of the final analysis. Unlike survey data, it is often difficult to tell the response rate for administrative data, such as the HIFLD data set which pulled information of childcare centers from each state's respective website. However, for data sets that rely on responses from business owners, such as the ZBP, it'd be helpful for the data collection agency to provide item nonresponse since they would have an idea who didn't respond to the questionnaire. This, although not a direct measure to reduce nonresponse, allows users to judge the completeness of the data on which the survey estimates are based.

Enhancing QC procedures to ensure internal consistency

This could especially benefit data users of the CCD and Head Start data, where lack of data consistency or confusion exist within each data set. It would be ideal to make sure that variables that overlap in some ways describe the construct in a consistent way. Or, at least, explain or note the inconsistency in an official public facing document, so that data users can make informed decisions about how to use such data.

Providing codebooks to help data users understand the variables/constructs better

Unlike survey data, such as the ECLS-K:2011 which provides detailed data user manuals, codebooks, and psychometric reports to describe the data and variables, administrative data are rarely accompanied by such documents. Therefore, it is left to the data users to guess how the variables and constructs are created and should be interpreted. A codebook where the variables/constructs are described, labeled, and coded could be a standard document available for anyone interested in using the administrative data set. The CCD could be a good starting point since there are already established data review procedures.

Aligning with research needs

Misspecification arises in several of the administrative data sets where what is measured in the data set is not ideally what the data users are looking for. This may not be an easy fix as it would require extra efforts to communicate with the research community, which may not be possible given the constraints of capacity and resources facing the data collection agency. In this case, again, documentation noting where the discrepancy lies would be helpful.

Building interagency collaboration to increase data compatibility and usability

In the patchwork type of landscape of early childhood education provision and data sources, building interagency collaboration to increase data compatibility and usability can be an important first-step to bring data sets into better alignment, and increase data visibility among potential data users. This not only can make data more user friendly, but it could also contribute to making the data more research relevant as the agencies share knowledge and resources about these data.

6.3 Future Research Questions

Moving forward, future researchers interested in children of immigrant parents could consider further exploring the following three directions. First, there is more to understand how variability in the likelihood of center participation is associated with key constructs from the spatial assimilation theory, such as family income, urbanicity of residential location, and immigration cohort. Second, since the supply of childcare centers, one of the childcare options in the private sector, could not seem to offset the negative impact associated with parental immigration status, researchers may want to examine what the public sector, such as state pre-K and Head Start programs, can do to improve the overall preschool participation rates among children of immigrant parents. Last but not least, it would make the analysis about childcare choices more comprehensive if future studies could include more alternative-specific measures, which are not currently available, such as cost of each childcare option, enrollment capacity, and distance from home for each childcare option the families have access to.

6.4 Conclusion

As one of the first studies to explore the relationship between childcare supply and childcare choices with a special focus on parental immigration status, this study combined multiple data sets to measure the supply of different childcare options. Findings from this study are concerning because children of immigrant parents seem to be worse off than peers with U.S.-born parents with regards to socioeconomic attributes, as illustrated by the descriptive statistics, which are predictors of not only childcare choices but also school readiness levels. Policy makers and researchers alike need to explore other aspects on the supply side to better understand what aspects and how they affect childcare choices by parental immigration status. While the GIS has been proved to be a helpful tool in merging data sets based on geographic information embedded within each data set, these early childhood education data sets themselves can be improved to provide more accurate and relevant data. With improved data, both in terms of quantity of other supply-specific measures and quality, one can better ensure that we understand the assets and liabilities afforded, in terms of childcare options/access, to all children.

APPENDIX A TECHNICAL REPORT

A.1 Introduction

This Technical Report documents details of the various administrative and survey data sets—the CCD, ECLKC, HIFLD, ZBP and ACS—that are used to supplement data in the ECLS-K:2011. The merits of using these data sets for this current study has been discussed in the Methodology chapter in this dissertation. This Technical Report instead focuses on describing (1) the data quality, as these data sets, most of which are administrative records, have not been widely used in prior education research or are less known to education researchers, (2) spatial join procedures to link these data sets and the ECLS-K:2011 data, and (3) details of auxiliary analyses and relevant statistics, such as model fit tests, measures of fitness, and sensitivity analysis.

Using administrative data presents several advantages. Administrative data, in general, are readily available on the respective websites of data collection agencies. They are inexpensive to acquire and are computer readable. They can provide detailed program-specific data, and track programs and/or individuals over years. Administrative data typically include data on large samples of a population and larger samples allow for a greater number of options for statistical analyses. A given administrative data set can be made more useful when it is linked to other datasets of different types (e.g., health; income; educational) using geographic data such as zip code (Hotz, Goerge, Balzekas & Margolin, 1998; Statistics Canada, n.d.). Research using matched survey sample data and administrative data, such as this current study, can benefit from both worlds—the rich demographic details available from survey data combined with detailed programmatic data from the administrative records. However, these data sets should be used with caution as there are a number of limitations documented in the literature and encountered in this current study, as described below in more details. Recommendations of how to improve the data quality for future research are provided in Chapter 6 Discussion.

The remainder of this Technical Report is organized to address the following aspects that support the conditional logit analyses and results in the main dissertation:

- Data quality of these data sets (Section A.2),
- Spatial joins using ArcMap and missingness (Section A.3),
- Estimation methods and model evaluation (Section A.4), and
- Sensitivity analysis (Section A.5).

A summary of findings and recommendations from this Report is included in the Discussion chapter in the main dissertation.

A.2 Data Quality of Data Sets

Modeling a family's choice set requires the blending of data from multiple sources. The current study relies on four administrative data sets and one survey data to supplement data from the ECLS-K:2011 data. These data sets provide information on three types of variables: the supply of and demand for childcare, and community characteristics. The CCD, HIFLD, ZBP and data from the ECLKC measure the supply of childcare. The ACS provides a proxy of the demand for childcare and measures of select community characteristics. In this section, an overview of each data set is provided, followed by a description of the data processing procedures to fit the data for this current study. Under each data set, issues of misspecifications are also listed (see Table A.1). These include data inconsistency, nonresponse, lack of research relevant data, and lack of study relevant data, pointing to potential areas for data quality improvement.

Inconsistency refers to inconsistent information provided by different variables measuring the same construct within a data set. This issue is particularly evident in the CCD and ECLKC, causing confusion to data users as to which variable should be considered as a reliable source for the construct of interest. **Nonresponse** happens when data are simply not reported back to the agency by an individual or a state agency responsible for providing the information. This is checked for the CCD as it had severely limited data in three states (California, Michigan, and Oregon). Although nonresponse is common among administrative data, the data collection agencies are often unable to estimate rates of nonresponses. **Lack of research-relevant data** refers to differences in concepts between what the administrative data collect and what the data users want to use. This is discussed in the specific context of this current study, though it is not uncommon in the use of administrative data in general. In other words, misalignment in concepts between administrative data and research use do exist, however, the extent to which the administrative data measurements deviate from research-relevant constructs varies from study to study depending on the specific research questions and constructs of interest. Finally, **lack of study-specific data** refers to embedded limitations of the administrative data sets to provide study-specific data for the current study. For example, the ECLKC, HIFLD and ACS fail to provide data for the specific school year, 2009-2010, while the ZBP, unlike the CCD and ECLKC, provides zip-code-level aggregate data rather than location-specific data (addresses).

Table A. 1 Issues of misspecifications

Source of measurement errors	**CCD**	**ECLKC**[1]	**HIFLD**	**ZBP**	**ACS**
Inconsistency	x	x			
Nonresponse	x				
Lack of research-relevant data	x	x		x	
Lack of study-specific data		x	x	x	x

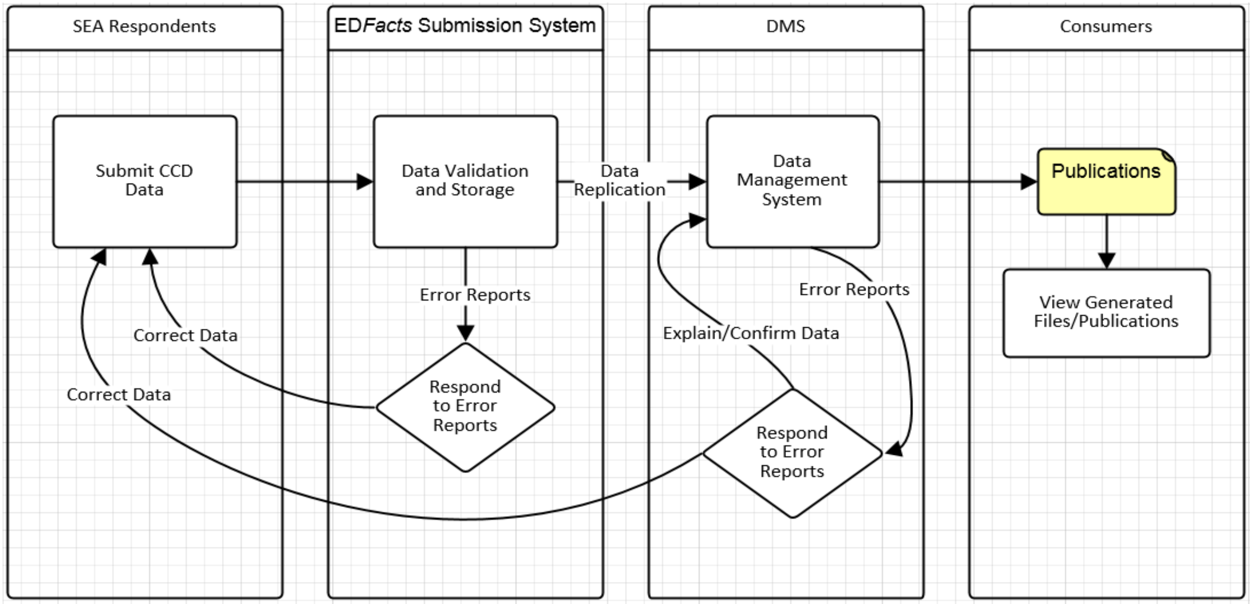
[1] This center provides two datasets to measure the supply of Head Start: Head Start Center Locations Datasets (HSCLD) and the Program Information Report (PIR), described in detail in section A.2.2 below.

A.2.1 Common Core of Data

The Common Core of Data (CCD) is the Department of Education's primary database on public elementary and secondary education in the United States. This program collects and publishes administrative data at the state, local education agency (LEA), and school levels. State education agencies submit data through the ED*Facts* Submission System online. The data are then processed in the Data Management System (DMS), an online system designed to manage the CCD collection, where states can review and respond to error reports, monitor data processing, and resubmit data files to resolve outstanding data issues. As illustrated in Figure A.1, the CCD go through a review process by CCD Data Analysts[8] for accuracy and rounds of correction by SEA respondents, as needed, before they are released to the public.

[8] The CCD data file is downloaded from NCES website: https://nces.ed.gov/ccd/pubschuniv.asp. There is another source to get the 2009-2010 CCD data, which is the NCES ElSi (Elementary and Secondary Information System): https://nces.ed.gov/ccd/elsi/. Conversation with a CCD Data Analyst informed me to use data from the first link for better data quality.

Figure A. 1 CCD data flow from initial state submission to publication



Source: U.S. Department of Education ED*Facts* Technology and Support Services (ETSS) II DMS State User Guide (DMS Release 2.0). Available at: https://www2.ed.gov/about/inits/ed/edfacts/index.html

The processing procedure I used with the CCD was fairly straightforward. I first checked duplicate cases by latitude and longitude, as these geographic coordinates were included in the public-use file. 186 duplicate cases were randomly deleted so that one record for each case remained in the final data file. The final CCD data file to be linked to the ECLS-K:2011 contained 27,732 public schools with state pre-K programs across 47 states and the District of Columbia (excluding California, Michigan, and Oregon) during the 2009-2010 school year.

Inconsistency

There are two variables in the CCD file that can be used to identify schools that offered the pre-K grade during the 2009-2010 school year. Variable `GSLO09` refers to "school low grade offered" and has five value labels: UG, PK, KG, 01-12, and N. "PK" indicates that the lowest grade offered at the school is pre-K. The other variable, `PK09`, provides enrollment in the pre-K grade at each school. In some cases, values for these two variables are not consistent. For example, among all schools where `GLSO09=PK` (low grade offered at school is pre-K):

- 3 cases have `PK09=-9`, indicating the data reported for `PK09` (pre-K enrollment number) are suppressed by NCES because they didn't meet the NCES data requirement;
- 93 cases have `PK09=-1`, indicating a value was expected but none was measured; and
- 2918 cases have `PK09=0`, showing the actual pre-K enrollment number was 0.

I decided to use the variable `GLSO09` as the authority in determining if a school offered the pre-K grade during the 2009-2010 school year. In other words, as long as the school's lowest grade was pre-K, such cases remained in the final data set to be counted as the supply of state pre-K for the ECLS-K:2011 sample, regardless of the value of variable `PK09`.

Nonresponse

Three states—California, Michigan and Oregon—submitted severely limited pre-K data of their state pre-K programs to the CCD: only 3 schools in California reported having a pre-K grade, 30 schools in Michigan, and 22 schools in Oregon. The reasons for nonresponse from these three states differ[9]:

- California: The state pre-K program is administered by the state health and human service departments, instead of the state department of education that responds to the CCD annual data collection. In other words, the CCD corresponding agency in California did not administer the pre-K program, therefore, had no data to report.
- Michigan: It is possible that state pre-K program in the state is mostly offered in non-school settings, therefore, there were outside the public school systems which are the main CCD data collection units.

[9] Information about Michigan and California was obtained from correspondence with the CCD officer at NCES, available upon request.

- Oregon: The Oregon Pre-K program is offered jointly with Head Start programs, mostly in non-school settings (Oregon Department of Education, n.d.), a similar situation as Michigan

I considered data in the CCD from the 2008-2009 and 2010-2011 school years, and found data were missing in the three states as well. Therefore, I decided to exclude California, Michigan and Oregon from this study because imputation was not appropriate when data for the whole state were missing or in question[10].

Lack of research-relevant data

As noted above, the CCD does not include state pre-K programs offered in non-school settings. This contributes to the last issue of misspecification: lack of research-relevant data, a limitation embedded in the CCD data collection design itself. Ideally, I would prefer state pre-K data that include programs offered at all types of settings, school and non-school alike. According to the State of Preschool Yearbook 2010, enrollment in state pre-K at public schools accounted for only 65 percent of all pre-K enrollment nationwide. Nearly 35 percent of children attended state-funded pre-K in settings such as Head Start classrooms, childcare centers, family childcare homes, or other community-based centers during the 2009-2010 school year (Barnett et al., 2010). This suggests that the CCD can only measure the supply of state pre-K for about 65 percent of all children enrolled in the programs nationwide.

In addition, the CCD does not collect data on program schedule. State pre-K program may run on different schedules, allowing the same class to be offered twice during the day at the

[10] The HIFLD data could be a potential data source to supplement the CCD on state pre-K offered in public school settings. However, it turns out that this data set also contains limited records of state pre-K located in public schools in California (160), Michigan (0) and Oregon (1). For cases in California, I crosschecked records in the HIFLD and respective school district websites and found significant discrepancy between the two sources. Therefore, these three states are excluded from the final data analyses.

same locations, for example, one AM class in the morning and one PM class in the afternoon. Ideally, locations with an AM and a PM class could be counted as two opportunities for eligible children. Because the CCD does not collect schedule information, all state pre-K locations recorded in the CCD are counted as one class in this study. Together, it is fair to say that the CCD provides an undercount of the supply of state pre-K program for this current study.

A.2.2 Early Childhood Learning and Knowledge Center

The Early Childhood Learning and Knowledge Center is a data source center within the Administration for Children and Families (ACF) at the U.S. Department of Health and Human Services (DHHS). It provides a comprehensive array of information on Head Start, ranging from grants and oversight, policy and regulation, and collaboration and partnerships, to data and reports. I used two sets of administrative data it offers—the Program Information Report (PIR) and Head Start Center Locations Datasets (HSCLD)—to identify locations of Head Start programs that operated during the 2009-2010 school year. The two data sets supplemented each other to meet the special data requirements for this current study: that data must be both location-specific (program address) and year-specific (2009-2010).

The PIRs are *annual* mandatory surveys of all Head Start grantees. The surveys collect detailed information on the services, staff, children, and families served by Head Start and Early Head Start grantees nationwide. These grantees may use federal funds to directly operate Head Start centers or provide some of the grant funds to other organizations, called "delegates" that directly operate centers to serve children and their families. The HSCLD, on the other hand, contains a list of all *current*[11] Head Start centers whose directors can input their addresses into

[11] The HSCLD data were downloaded in February 2017 in excel format from: https://eclkc.ohs.acf.hhs.gov/about-us/article/head-start-center-location-datasets. It was not clear, however, when the Head Start location information was collected.

this online database. In order to identify Head Start centers that were operational during the 2009-2010 school year, I matched individual centers (location-specific) from the HSCLD with the year-specific (2009-2010) grantee records in the PIR.

The data processing procedure included a few steps. First, Early Head Start programs were dropped from both the PIR and the HSCLD because they only enroll children age 3 and under and were not age-eligible for this study. In the PIR, the Early Head Start programs were identified by the variable `ProgramType`, categorized as `EHS`. In the HSCLD, they were identified by the variable `centertype`, categorized as `Early Head Start`. Additionally, several Early Head Start records in the HSCLD were also identified by variables `grantee` or `name`, as the term “early head start” or “EHS” appeared in the variables.

Second, as with the CCD, records were checked by latitude and longitude coordinates, and duplicates were randomly excluded. In the HSCLD, some cases shared the same location but carried a second identifier— for example, center #1 and/or center #2, or suite A and/or suite B. A case like this—same address but different second identifies—could be potentially counted as several individual Head Start locations, as these locations were either several individual buildings (as Google Map shows) or individual suites within the same building. To be consistent with the CCD editing criteria: whether a location offers a particular type of childcare option rather than its enrollment capacity, I randomly deleted duplicates with the same latitude and longitude coordinates but different second identifiers from the HSCLD so that each case corresponded to one unique set of latitude and longitude coordinates. This deleted 191 cases.

The final step was to match individual centers from the HSCLD (location-specific) with the year-specific (2009-2010) PIR grantee records. This was to make sure that the individual center(s) identified in the HSCLD was associated with a grantee (in the PIR) that was operational in the 2009-2010 school year. I attempted to merge on the variable `grantnumber` which was available in both files. In the PIR, it had 8 digits, however, in the HSCLD, it had 8 or more digits, therefore, can not be used to merge the two files[12]. Instead, I used the program zip code variable in both files to merge them, and spot checked every 50 cases to ensure the grantee's name from both files matched. This process resulted in 11,642 cases in the HSCLD matched to the PIR records. These cases contained both address and latitude and longitude information, and the latitude and longitude were used as the key geographic linkage in the merging with the ECLS-K:2011 data. In addition to these matched cases, there are 561 cases in the PIR that did not have a match in the HSCLD. They could be programs that were operational during the 2009-2010 school year but failed to renew in the following years. These cases only had address information which was then geocoded into latitude and longitude for the spatial join, described more in detail in section A.3. Altogether, the final Head Start data set to be merged with the ECLS-K:2011 data included 12203 Head Start locations.

Inconsistency

Similar to the CCD, the HSLCD and the PIR data sets each had variables with inconsistent information. The HSLCD had two sets of location information: 1) address, city, state and zip, and 2) latitude and longitude. Among some cases with the same latitude and longitude, the address variable was different or contained a P.O.Box. I decided to use latitude and longitude, instead of address, as the location authority for two reasons. First, some addresses contained a P.O.Box which was not an actual location where children can be cared for. Second, some addresses had both a P.O.Box and street number, and therefore, were confusing to use.

[12] The first 8 digits of the `grantnumber` variable in the HSCLD did not match those in the PIR file.

The address information in the PIR was messy as well. The PIR contained two variables `programaddressline1` and `programaddressline2`, documenting the program address. In most cases, `programaddressline1` contained a regular address with street number and street name, whereas `programaddressline2` contained secondary address information, such as a suite number. However, this did not apply to all cases. There were some cases where neither address line variables provided a physical address, but a P.O.Box and/or program name. For this reason, these cases were excluded from the study (n<30).

Lack of research-relevant data

There are two issues in the Head Start data that point to the lack of research-relevant data. First, among the 561 records that only existed in the 2009-2010 PIR, it was not clear whether the program location provided in the data file can be used as a location where childcare service was provided. The variable `programagencydescription` provides labels for how each program operates:

1) Delegate agency,
2) Grantee that delegates all of its programs; it operates no programs directly and maintains no central office staff,
3) Grantee that directly operates program(s) and has no delegates,
4) Grantee that directly operates programs and delegates service delivery, and
5) Grantee that maintains central office staff only and operates no program(s) directly.

PIR cases that fell under categories 2) and 5) were excluded from this current study because these programs and associated addresses provided in PIR were clearly not childcare service locations. It is unclear, however, whether the address information reported in the PIR for cases under category 3) were actual childcare service locations. There were 13 such cases under category 3, and they were retained in the final data set.

The second issue related to the lack of research-relevant data involves the ambiguity in the data label. As described in the previous CCD data section, some childcare providers may use combined funding sources from state pre-K and Head Start. In other words, it was possible that there were classrooms with children receiving services under both Head Start and state pre-K programs. In the matched Head Start data file, there were approximately 1,800 cases whose grantees were labeled as `School System`[13]. These grantees were either delegate agencies or grantees that directly operated programs. Ideally, some of these cases could also be added to the CCD data file if they were located at public schools and enrolled children who were funded by the state. However, these Head Start locations did not match any record in the 2009-2010 CCD file by latitude and longitude. Since the CCD were 2009-2010 year-specific, not having these schools in the CCD may indicate that these Head Start locations did not become operational until after the 2009-2010 school year. Additionally, it was not clear from the data source if these Head Start grantees that were school systems actually enrolled children who were funded by the state pre-K programs. Therefore, these cases were used to measure the supply of Head Start only.

Lack of year-specific data

The HSCLD data are not 2009-2010 year-specific, therefore, matching the Head Start centers in the HSCLD to the 2009-2010 PIR records may also lead to an overcount of the number of Head Start locations that were actually operational during the 2009-2010 school year. It was possible that some grantees had experienced expansion since 2009-2010, therefore, were

[13] Other grantee types include community action agency (CAA), government agency (non-CAA), private/public for-profit, private/public non-profit, and tribal government or consortium (American Indian/Alaska Native), in addition to school system.

matched to more *current* Head Start centers than they actually oversaw during the 2009-2010 school year. In other words, these grantees may have begun to oversee additional locations that became operational after the 2009-2010 school year. Given the limitations of the two data sets, it is not possible to tell which centers came to existence after the 2009-2010 school year.

A.2.3 Homeland Infrastructure Foundation-Level Data

The Homeland Infrastructure Foundation-Level Data (HIFLD) are collected, processed and shared by the HIFLD subcommittee established in 2002 within the U.S. Department of Homeland Security. Nested within the Education domain is the data set for Day Care Centers, which provides the address (physical and in longitudes and latitudes), enrollment, and type (center-based, school-based, Head Start, religious facility) of all day care centers for all 50 states, District of Columbia and Puerto Rico. Data were acquired from respective states departments or their open source websites by the HIFLD subcommittee. The HIFLD serves as data source for childcare centers across the country for this study.

The raw HIFLD data set contained a broader array of childcare settings beyond childcare centers for preschool-aged children. Therefore, the following exclusion criteria were applied because either these cases had been relatively comprehensively represented by other datasets described above, such as the CCD, the HSCLD and the PIR, or because these cases provided care for children of other ages:

- Head Start centers,
- State pre-K located at public schools,
- Youth services of any sort,
- Care provided for school-aged children (SACC, Boys & Girls Clubs, etc.),
- Care provided for infants and/or toddlers only, and

- Summer camp of any sort (YMCA, Rec and Parks, etc.).

I first used the variable `state_subt` to preliminarily drop some of these childcare options. This variable contains 170 categories of care type, such as “before and after school programs”, “infant/toddler”, “SACC”, “school age”, and so on. These descriptors helped me to eliminate some cases which provided care for children other than the preschool age group. Following the order of criteria listed above, I then conducted a thorough check using the variable `name`, literally the name of the childcare settings. It contained key words, such as “Head Start”, “after school extended care”, that helped to determine inclusion/exclusion for this study. Appling the criteria to eliminate inappropriate cases by variable `name` was a lengthy process. In the end, 84,047 childcare centers across 50 states and the District of Columbia that provided day care services for pre-school aged children were retained in the final HIFLD data. They measured the supply of childcare centers for the ECLS-K:2011 sample.

Lack of year-specific data

Unlike data from the CCD and ECLKC, which were both year- and location-specific, the HIFLD day care center data were only location-specific, which was the main quality concern of this data set. As shown in Table 4.2, the HIFLD dataset was updated in patches over the years. Therefore, it may be an overcount or undercount of the number of childcare centers in 2009.

A.2.4 Zip Code Business Patterns

The Zip Code Business Patterns (ZBP) is part of the County Business Patterns, a survey that collects economic data from owners of business establishments by industry annually. An establishment within each industry is classified by its physical location where some form of business activity is conducted; the owner of the establishment reports administrative data to the Census Bureau (U.S. Census Bureau, n.d.). Published primarily according to the 2007 North

American Industry Classification System (NAICS), the ZBP provides data on the number of businesses that are located within each zip code by employment size: 1-4 employees, 5-9 employees, 10-19 employees, with increasing increments to 500-1000 employees.

Relevant to the current study is the 2007 NAICS code 624410 for childcare services, defined as "an establishment primarily engaged in providing day care of infants or children." [14] According to the description of the childcare services industry on the ZBP website, these childcare establishments covered a wide array of childcare services, ranging from informal babysitting services at provider's home, family childcare homes, to formal day care centers, state pre-K, or Head Start centers that were not located within a public school. However, there was no further breakdown as to which employment size category corresponded to which type of informal or formal childcare service(s). Therefore, for reasons described in detail in the Methodology chapter, I decided to consider childcare establishments with 1-4 employees as family childcare homes. The final ZBP data file contained approximately 5800 unique zip codes within which the number of childcare establishments with 1-4 employees ranged from zero to ten.

Lack of research-relevant data

The ZBP data lack research relevance for two reasons. First, the ZBP is used in the current study to measure, ideally, the number of non-relative care providers. In reality, it only had data on the number of one non-relative care arrangement: family childcare homes. Therefore, it could be an undercount of all non-relative care providers which should also include individual care providers such as babysitters or neighbors. On the other hand, the ZBP data file did not differentiate between types of care or age group of children cared for. It is possible that

[14] For the 2007 NAICS definition of 624410 Child Day Care Services, go to: https://www.census.gov/cgi-bin/sssd/naics/naicsrch?code=624410&search=2007%20NAICS%20Search

there were FCC homes that providde exclusively afterschool care for school-aged children, rather than for preschool-aged children. Therefore, it could be an overcount of FCC homes for preschool aged children.

Lack of location-specific data

Unlike the three data sets discussed previously, data in the ZBP were aggregate numbers of childcare establishments within a zip code, rather than specific addresses. This made it easier to edit the data for this current study, but may lead to issues of either undercount or overcount.

A.2.5 American Community Survey

The American Community Survey (ACS) collects detailed information on the demographic, social, and housing characteristics from housing units and population across the country. I used the 2007-2011 ACS 5-year estimates at the census tract level. These estimates described the average characteristics in a census tract over a 5-year period with data collected from January 1 of 2007 to December 31 of 2011. The data file contained 74,001 unique census tracts and the following variables to account for the demand for childcare as well as select neighborhood characteristics: percent of children age 5 and under (conceptualized herein as an indicator of the community demand for childcare), percent of the population that is foreign-born, median household income, female labor force participation rate, and composite poverty rate.

Compared to the other data sets described above, the ACS has been more widely used by the research community. Researchers agree the ACS data are noisy, which has to do with the sample size and the mixed-mode sample design (U.S. Census Bureau, 2010). The noise is reported as margins of errors in the data set, informing data users about the degree of data uncertainty. It is common practice to improve data metrics either by collapsing cells or combining geographies of interest (Spielman & Folch, 2015). For the current study, I aggregated the percentages of all census tracts whose centroids fell within the buffers (see Section 4.3.2 in the mail dissertation for a brief description of the buffer) and used the averages to represent the demand of childcare and select community characteristics.

Lack of year-specific data

For the current study, the ACS 5-year estimates provided estimates of population averages over a 5-year period from 2007 to 2011, rather than 2009-2010 specific. This drawback is outnumbered by the advantages of using the 5-year estimates, as described in Section 4.1.5.2 in the Methodology chapter.

A.3 Spatial Joins using ArcMap and Missingness

These data sets measuring the supply of different childcare options, the demand for childcare, and select community characteristics are spatially joined to the zip code centroids of the ECLS-K:2011 sampled children in ArcMap 10.5. The CCD, ECLKC and HIFLD data were joined by addresses (latitude and longitude), the ZBP data by zip codes centroids, and the ACS data by census tract centroids. The final data file for the conditional logit analyses contains 7,106 children, living in 1,173 unique zip codes across the country. Three parameters around each sampled child's home zip code, 5 miles, 10 miles, and 25-minute drive, are drawn using two different tools in ArcMap: Buffer and Network Analyst. The Buffer tool in ArcMap 10.5 was used to create the two distance parameters (5 miles and 10 miles) and the Network Analyst tool was used to create the time parameter (25 minutes)[15].

To conduct point-to-point calculation using the Buffer and Network Analyst tools around the child's home zip code centroid, each piece of geographic information from these data sets, such as latitude and longitude coordinates, zip codes, and census tracts, needed to be located in the ArcMap system first. Therefore, two additional geographic information files were acquired from the UNC GIS service website; these files provided centroid points for all zip codes and census tracts in the U.S. in 2010, respectively. The zip code point file was linked to the ECLS-K:2011 sampled children's home zip codes and the ZBP data, giving each zip code a geographic location (zip code centroid). Similarly, the census tract point file was linked to the ACS data, giving each census tract a geographic location, defined by the census tract centroid.

Both spatial join functions allowed me to define an area, the buffer, and produce various statistics of interest within the specific area, such as the aggregate number of each childcare

[15] A helpful tutorial that shows the difference between Buffer and Network Analyst is here: https://www.youtube.com/watch?v=4E4ZqGLIKxI

option, the average percentage of children age 5 and under (demand for childcare), and the average community characteristics. The two tools differed in how the buffer was defined.

A.3.1 Buffer Tool for distance parameters (5- and 10-mile models)

The Buffer tool drew a circle around each sampled child's home zip code centroid with the radius set to a specific value. It counted the point-to-point distance with one key point being the child's home zip code centroid, and included only geographies located within the buffer for further calculation of statistics of interest. The geography, or the other point used for the point-to-point calculation, differed by data set. For the CCD, ECLKC and HIFLD data which had latitude and longitude coordinates, the geographies were specific addresses of state pre-K programs, Head Start centers, and childcare centers, respectively. For the ZBP data, they were zip codes centroids, and for the ACS data, the census tract centroids.

A.3.2 Network Analyst for commute time parameter (25-minute model)

The time parameter was created using the Network Analyst tool, which highlighted streets within a 25-minute drive around each study child's home zip code centroid in all possible directions. This created a service area, a region that encompassed all accessible streets within the specific travel time (25 minutes) from a particular point (sampled child's home zip code centroid). Similar to the functionality of the Buffer tool, the Network Analyst includeed cases for further calculation only if the addresses (of the CCD, ECLKC and HIFLD), zip code centroids (of the ZBT) or census tract centroids (of the ACS) fell within the service area. On the other hand, unlike the parameters created by the Buffer tool, which was a perfect circle, this time-parameter was based on physical streets, therefore, did not take a regular shape.

A.3.3 Missingness and data decisions

These spatial joins using ArcMap to link administrative data sets to the ECLS-K:2011 sample's zip code centroids revealed some unexpected missingness issues. Multiple imputation was conducted to handle missing data in some of the administrative data sets if the missingness would affect a significant portion of the study sample. On the other hand, zip code missingness was not imputed. This is because the home zip code was the key geographic unit that determines the buffer location for the childcare supply, demand, and community characteristics. Any imputed zip code value may either alter the buffer location to the extent that it may lead to significantly different supply, supply, and community characteristics, or it may result in non-existent zip codes, as described below.

Missingness and multiple imputations

The final ECLS-K:2011 sample contained only complete cases. However, missingness was evident in the CCD, ECLKC, HIFLD, and ZBP data after they were spatially joined to the ECLS-K:2011 sample, in the sense that some cases in the ELCS-K:2011 sample would have a missing value for the supply of a particular childcare option or community characteristics. For example, in the 5-mile model, nearly 30 percent of the unique home zip codes from the ECLS-K:2011 sampled children did not have a value for the number of childcare centers after the HIFLD data were spatially joined, which may indicate that no childcare centers were available within 5 miles of these home zip codes. In order to check if this was the case, I checked changes in the missing rates as the buffer size changed, as shown in Table A.2.

The missing rate referred to the percentage of unique home zip codes that do not have a value from each respective data set. As the buffer radius increased from 5 miles to 10 miles, missing rates in the CCD, ECLKC, HILFD, and the ZBP decreased by five to ten percentages.

The 25-minute model had the lowest missing rates across the three models. This may suggest that data may be non-existent, indicating the supply of that specific childcare option was zero around these specific home zip codes. Spot checks were conducted in Google Map to verify if the supply of certain childcare options was limited around these zip codes. Non-existent data on the numbers of state pre-K, Head Start, childcare center or family childcare homes were impossible to impute and therefore, were replaced with zeroes. Missing values from the ACS were imputed because each census tract should have demographic information such as those needed for this study.

Table A. 2 Percentages of missingness by buffer size.

Data set	**Measure**	**Buffer size**			**Number of imputation**	**Variables used for imputation**
		5 miles	**10 miles**	**25 min.**		
CCD	State pre-K	29.46	18.79	15.49	n/a	n/a
ECLKC	Head Start	30.49	11.49	5.64		
HIFLD	Centers	29.39	24.36	21.75		
ZBP	FCC homes	31.80	16.00	10.46		
ACS	Demand for childcare and community characteristics	10.00	9.00	8.6	50	zip code population, zip code population per square miles

Note: Missingness percentages are calculated after each data set is spatially joined to the unique home zip codes from the ECLS-K:2011 sample (N=1173).

I used the chained equation/MICE (also known as the fully conditional specification or sequential generalized regression) to impute missing data in the ACS describing the demand for childcare and select community characteristics. This imputation option allowed a separate conditional distribution for each imputed variable, such as binary, ordered and multinomial logistic regression for categorical variables, linear regression and predictive mean matching for continuous variables, and Poisson and negative binomial regression for count variables (StataCorp LP, 2013). I used linear regression to impute continuous variables, such as the average percentages of children less than five, and select community characteristics.

Multiple imputations were performed on 1,173 cases with unique home zip codes after measures of the supply of and the demand of childcare and select community characteristics had been linked together. Given some of the missing rates, the number of imputations was set to 50, and two auxiliary variables—zip code population and zip code population per square mile—were used to impute the missing values (see Table A.2). Since the multiple imputation command in Stata does not support the conditional logit model, I calculated the mean of each imputed variable after multiple imputation and merged them with the ELCS-K:2011 sample to be used in the conditional logit model (more details about Stata commands are provided in Section A.5).

Missingness due to zip code issues

I had to exclude 157 cases that have complete case information from the final ECLS-K:2011 sample due to zip code issues. Using the Buffer tool in ArcMap revealed that a set of 13 unique zip codes appear to be non-existent zip codes as they were not found in any GIS zip code maps. This means that their zip code centroids can not be located in ArcMap for further spatial joins. This affected 21 cases with complete case information in six states in the ECLS-K:2011 sample. Another set of 136 cases among 23 states with complete case information in the ECLS-K:2011 did not provide a home zip code. The school zip codes were available for these cases, however, I decided not to use them as a proxy for home zip codes. Zip codes in this current study were key geographic units that linked the administrative and survey data to the study children. Any proxy zip code may either alter the buffer location to the extent that it leads to significantly different supply, demand, and community characteristics, or it could result in non-existent zip codes.

I conducted t-test between cases that did not provide a zip code (N=136) and those with zip code information (N=7106). These tests suggested that these two groups did not differ much with respect to child and family characteristics except for immigrant-related measure. For example, among cases that did not have zip code information (N=136), approximately 30 percent of them were households with at least one immigrant parent whereas the percentage for cases that had zip codes (N=7106) was only 10. This may indicate that zip codes can be sensitive information that immigrant parents were not willing to share.

A.3.4 Summary of Data Merging Results

To sum, the core data for this study included 7106 children living in 1173 unique zip codes from the ECLS-L:2011 (Table A.3). These cases not only had complete information on all variables needed for the CL analyses, but also had valid zip codes allowing spatial joins with the other data sets. The pool of data that were spatially joined to supplement child and family characteristics in the ECLS-K:2011 included the following: 27732 public schools with pre-K grade from the CCD, 12203 Head Start locations from the ECLKC, 84047 childcare centers from the HIFLD, FCC data from 5800 unique zip codes from the ZBP, and demand for childcare and select community characteristics from 74001 unique census tracts from the ACS.

Table A. 3 Summary of data set attributes relevant to data merging process.

Data source	Sample size for spatial joins	Construct	Linking geography
ECLS-K:2011	7106 sampled children (1173 unique zip codes)	Supply of parental and relative care; Child and family characteristics	Zip code centroid
CCD	27,732 public schools with pre-K grade (excluding CA, MI, and OR)	Supply of state pre-K	Address
ECLKC	12203 Head Start locations	Supply of Head Start	Address
HIFLD	84,047 childcare centers	Supply of childcare centers	Address
ZBP	5800 unique zip codes	Supply of FCC homes	Zip code
ACS	74001 unique census tracts	Demand for childcare; Select community characteristics	Census tract centroids

A.4 Estimation Methods and Model Evaluation

I used the Stata command `asclogit` which fit the McFadden's choice model, a specific case of the more general conditional logistic regression model, in this study. This command requires multiple observations for each child, where each observation represents a childcare option that may be chosen. Therefore, after the childcare supply data and the community characteristics information were spatially joined with the ECLS-K:2011 sample, I changed the data arrangement from wide to long. As shown in Table A.3, in the long format, each child had six rows of observations, each corresponding to a childcare option that could potentially be chosen (under the column "childcare options"). The third column, "observed choice", indicates which care option was the actual childcare choice during the year prior to kindergarten assigned the value 1, otherwise 0.

As described earlier, `asclogit` allowed two types of independent variables: alternative-specific variables, which varied across both cases and alternatives, and case-specific variables, which vary across cases only. In this study, the alternative-specific variable was the number of childcare options available to the child, as shown in the fourth column, "number of childcare options", in Table A.4. For child 1, for example, there was no other childcare options other than parental care within 5 miles of the family's home zip code. For child 2, there were 13 centers, one Head Start center, three state pre-K locations, and one FCC home within 5 miles. The case-specific variables were child, family and community characteristics that only varied across individual children but not across childcare options for the same child, such as the two variables in the last two columns in Table A.4. For child 1, the family had an income of $25001-$50000 whereas child 2 lived in a family with an income above $75001. The highest parental educational level was the same for the two children (high school graduates).

Table A. 4 Example of data arrangement, alternative-specific and case-specific variables in the long format (5-mile model).

Child ID	Childcare options	Observed choice	Number of childcare options	Family income	Parental education
1	center	0	0	$25001 - $50000	High School Graduates
1	head start	0	0	$25001 - $50000	High School Graduates
1	state pre-K	0	0	$25001 - $50000	High School Graduates
1	non-relative	0	0	$25001 - $50000	High School Graduates
1	relative	0	0	$25001 - $50000	High School Graduates
1	parental	1	1	$25001 - $50000	High School Graduates
2	center	1	13	$75001 and more	High School Graduates
2	head start	0	1	$75001 and more	High School Graduates
2	state pre-K	0	3	$75001 and more	High School Graduates
2	non-relative	0	1	$75001 and more	High School Graduates
2	relative	0	0	$75001 and more	High School Graduates
2	parental	0	0	$75001 and more	High School Graduates

Smithson and Merkle (2014) summarize three evaluative and diagnostic procedures to fit and evaluate generalized linear models: goodness-of-fit tests, inspecting residuals, and goodness-of-fit measures, which apply to the CL models. Using various tests in Stata, I fit conditional logit models, tested model fits for the three buffer sizes, and described the procedures below. I also noted alternative commands in Stata to use after the `asclogit` command, where applicable, as some Stata post estimation commands for binary models will not work after `asclogit`. However, as Smithson and Merkel (2014) point out, unlike for binary models, model evaluation and diagnosis in multinomial models is still an active area of research, even though inference methods for these models are well established.

A.4.1 Goodness-of-fit tests

Three statistics were helpful in determining model fit and gauging whether one model fit the data better than the other for the CL model: the link test, AIC and BIC. I started the model tests with the basic model that includes pre-selected variables based on existing literature and theories. The first step was to conduct a link test. The link test was based on the idea that if an equation was properly specified, there should be no additional independent variables that were significant except by chance. For a model where $y = f(X\beta)$ and $\hat{\beta}$ represented the parameter estimates, the Stata command `linktest` calculateed:

$$\_hat = X\hat{\beta} \text{ and } \_hatsq = \_hat^2$$

The model is then refit with $\_hat$ and $\_hatsq$, and the key statistic is the significance of $\_hatsq$. The variable $\_hat$ should be a statistically significant predictor, since it is the predicted value from the model, while the variable $\_hatsq$ shouldn't have much predictive power except by chance. Therefore, if $\_hatsq$ is significant, then the link test is significant. This usually means that there are omitted relevant variable(s) or the link function is not correctly specified (see also Pregibon, 1979; Tukey, 1949).

Since the link test can be applied to only single-equation estimation techniques, it does not work with the `asclogit` command, so I manually calculated the $\_hat$ and $\_hatsq$ values after the `asclogit` command:

```
predict _hat, xb
gen _hatsq=_hat^2
asclogit choice _hat _hatsq, case(childid)
alternatives(cc_options)
```

where `choice` was the dependent variable and `cc_options` the six childcare options. This step was repeated for models with interactions and higher forms.

When the link test was not significant— a desired result of model specification tests— the next step was to conduct the log likelihood ratio test using the Stata command `lrtest`. The LRT compares the maximized log-likelihoods of the two models under consideration. The idea is that the full model's log-likelihood is always larger than that of the reduced model, because the former has more parameters. However, given issues of overfitting and model inflation effects that are more likely to happen for multinomial models than for their binary counterparts (because the number of cells in a model more rapidly proliferates as predictors are added to the model), it is recommended that information criterion measures such as the Akaike information criterion (AIC, Akaike, 1974) and Bayesian information criterion (BIC, Schwarz, 1978) be used when comparing complex models that differ only in one predictor (Smithson & Merkle, 2014). The two statistics are defined as follows:

$$\text{AIC} = -2logL\left(\hat{\theta}\middle|y, X\right) + 2q$$

$$\text{BIC} = -2logL\left(\hat{\theta}\middle|y, X\right) + qlogn$$

The AIC measures the fit of the model via the likelihood. The BIC then penalizes the model for complexity (measured by the number of free parameters, q). I used the `lrtest` command to obtain the AIC and BIC. The model with the lowest values of AIC and BIC statistics was considered the "best", providing a better fit after accounting for its number of free parameters.

The three statistics from the link test and the LR tests revealed that, for the current study, consistent across the three buffer sizes, the basic model with pre-selected predictors had the lowest values for both AIC and BIC than models with either interactions and/or higher forms, although smaller log likelihood. Therefore, I decided to use the basic model for the CL analyses. This was a more conservative approach due to concerns of overfitting and model inflation effects of the multinomial models. Next, I tested the model fit for the three buffer sizes by inspecting residuals and examining goodness-of-fit measures, described below.

A.4.2 Inspecting residuals

Assessing fit involves both the analysis of the fit of individual observations and the evaluation of scalar measures of fit for the model as a whole (Long & Freese, 2014). Regarding the former, the residuals and residuals plots are helpful in the context of CL models (Smithson & Merkle, 2014). The raw residuals are $y_{ij} - \hat{\pi}_{ij}$, where y_{ij} is the childcare choice variable, taking the value 1 if the j^{th} childcare option was the chosen childcare arrangement during the year prior to kindergarten and 0 otherwise, and $\hat{\pi}_{ij}$ is the predicted probability of using the j^{th} childcare arrangement during the year prior to kindergarten for the i^{th} child. Keep in mind that the data were arranged in a long format for CL models where each child corresponded to j rows of observation (J=6) representing different childcare options, see Table A.5. The predicted probability of using parental care for child 1 was 0.449 and the residual was 0.551. For child 2 who was enrolled in center care during the year prior to kindergarten, the predicted probability of using center was 0.499 and the residual was 0.501. Between the two cases, the model predicted the probability of choosing center care slightly better than that of choosing parental care. For the key independent variable—number of childcare options—I plotted the residuals by buffer size in Figure 5.1, and discussed their implications in Section 5.3 of the Findings chapter.

A.4.3 Goodness-of-fit measures

In addition to inspecting and plotting residuals, many scalar measures have been developed to summarize the overall goodness of fit of the models. Measures of fit for the CL models are presented in Table A.6. They provide a rough index of whether the three models were adequate. As Long and Freese (2014) point out, measures of fit provide valuable information about the model fitness, but it is only partial information and should be assessed within the context of the theory, past research, and the estimated parameters of the model being considered. A single value of a given measure can not be used alone to determine the model fit.

Table A. 5 Observed and fitted probabilities and residuals of CL model (5-mile model).

Child ID	Childcare options	Observed choice	Number of childcare options	Predicted probability	Residual
1	center	0	0	0.100	-0.100
1	head start	0	0	0.050	-0.050
1	state pre-K	0	0	0.266	-0.266
1	non-relative	0	0	0.020	-0.020
1	relative	0	0	0.116	-0.116
1	parental	1	1	0.449	0.551
2	center	1	13	0.499	0.501
2	head start	0	1	0.027	-0.027
2	state pre-K	0	3	0.120	-0.120
2	non-relative	0	1	0.089	-0.089
2	relative	0	0	0.163	-0.163
2	parental	0	0	0.100	-0.100

Among these measures displayed in Table A.6, the log likelihood, Wald chi-squared and the p-value were direct outputs from the conditional logit model estimations. The McFadden and McFadden adjusted R-squared statistics were calculated using the following two equations.

McFadden's R^2:

$$R^2 = 1 - \frac{ln\hat{L}(M_{full})}{ln\hat{L}(M_{null})}$$

McFadden's adjusted R^2:

$$R^2_{adj} = 1 - \frac{ln\hat{L}(M_{full}) - K}{ln\hat{L}(M_{null})}$$

Where $ln\hat{L}(M_{full})$ denotes the log likelihood of the full model, $ln\hat{L}(M_{null})$ the log likelihood of the intercept-only null model, and K the number of predictors.

McFadden's adjusted R^2 mirrors the adjusted R^2 in OLS by panelizing a model for including too many predictors. If the predictors in the model are effective, then the penalty will be small relative to the added information of the predictors. However, if a model contains predictors that do not add sufficiently to the model, then the penalty becomes noticeable and the adjusted R^2 can decrease with the addition of a predictor, even if the R^2 increases slightly. McFadden's adjusted R^2 tend to be considerably lower than those of the R^2 index, for example, values of 0.2 to 0.4 represent excellent fit (McFadden, 1979). These R^2 statistics are reported in Table A.6, showing that the models were not excellent fits, while the 5-mile model seemed to fit slightly better than those of the other two buffer sizes. Looking at the AIC and BIC statistics, however, the 10-mile model had the smallest AIC and BIC values. Nevertheless, none of these statistics suggest that one particular model was significantly better than the other two models.

Table A. 6 Model fitness parameters by buffer size.

Measures of fit for CL models of childcare choice	**5-mile**	**25-minute**	**10-mile**
Log-likelihood	-10052.42	-10051.41	-10537.73
Wald $chi^2(186)$	2851.28	2851.66	2662.8
Prob>LR	0	0	0
McFadden's R^2	0.153	0.153	0.153
McFadden's adjusted R^2	0.150	0.149	0.149
AIC	20866.85	20864.82	20856.65
BIC	24166.48	24164.46	24156.28

A.5 Sensitivity Analysis

In this section, I reported estimated coefficients, marginal effects, predicted probabilities based on the final CL models of the three buffer sizes. These estimations are standard sensitivity analysis statistics for general linear models, in general. The technical content herein is referenced to Long (2016), Long and Freese (2016), and Smithson and Merkle (2014).

A.5.1 Estimated coefficients

Although the odds ratios are often reported in the main finding section for general linear models, the estimated coefficients show unit and standard deviation change in independent variables. The full sets of estimated coefficients for the three models were reported in Appendix B. The coefficient for `num` indicated the effect of the number of childcare options on the log odds when an alternative was selected. A positive coefficient indicated that the chances of an alternative being selected increased as the number of that childcare alternative increased. Otherwise, a negative coefficient indicated that the chance of an alternative being selected decreased as the number of that childcare alternative increased. By default, the base alternative was the most frequently chosen alternative. In this study, I changed it from center to parental care, because I was interested in knowing how the key variables affected the probability of choosing center care. The estimate coefficient for `num` in Tables B.1 through B.3 was $.050^{**}$, $.008^{**}$, and $.029^{**}$ for the 5-mile, 10-mile, and 25-minute models, respectively, and all coefficients were statistically significant at the .01 level. This indicated a positive relationship between the number of childcare options and choosing that particular care option.

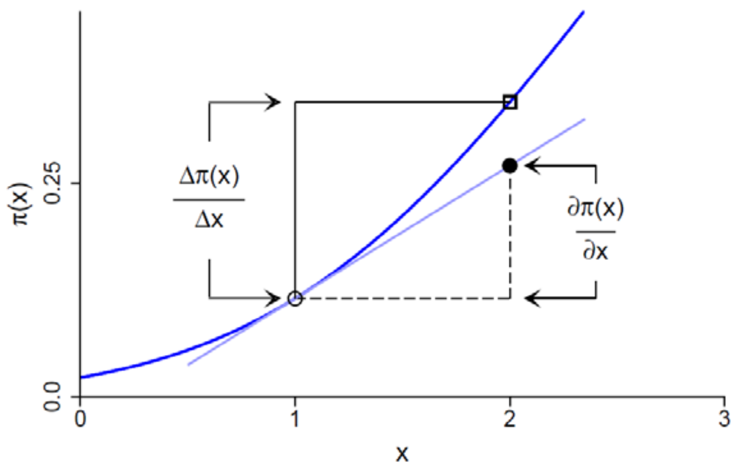
A.5.2 Marginal effects

Marginal effects are an informative means for summarizing how change in a response is related to change in a covariate. They measure the instantaneous rate of change, as summarized in the equation below.

$$ME = \frac{\partial \pi(x)}{\partial x}$$

Where $\pi(x)$ is the predicted probability, x is the independent variable, and the marginal effect is interpreted as the additive change in probability for one-unit change in x_k holding other variables at specific values, as illustrated by $\partial \pi(x)/\partial x$ in Figure A.2.

Figure A. 2 Marginal effects and discrete change



Source: Long (2016).

For a binary independent variable, the marginal effect measures discrete change—how $\pi(x)$ changes as the categorical variable, x_k, changes from 0 to 1 (x_k: end = 1, start = 0), holding all other variables at their means. For categorical variables with more than two values, e.g., parental education, the marginal effects show the difference in the predicted probabilities for cases in one category relative to the reference category. For example, in the current study, parental education was coded 1 = less than high school, 2 = high school graduates, 3 = bachelor’s degree, 4 = advanced degree. If “1 = less than high school” was the reference group, the marginal effect for “2 = high school graduates” would show how much more (or less) likely parents with a high school diploma were to choose a certain childcare option (e.g., center) than were parents who didn’t graduate from high school.

For continuous variables, the function is the same except that caution is needed when interpreting marginal effects and the unit of change. By default, the marginal effects are calculated based on the variable means. If one is interested to find out how a unit of change in the child’s age would affect the likelihood of choosing center, the average child’s age was 4.5 years. It was statistically correct to say that one-unit change in age (1 year) is more (or less) likely to increase/decrease the probability of choosing a childcare option. However, the majority of children at age 5.5 are most likely to be enrolled in kindergarten than preschool, therefore, rendering this estimate less appropriate.

In Stata, the command `estat mfx` is used to obtain marginal effects after the `asclogit` command, instead of `margins`. It provides predicted probabilities and marginal effects, holding all variables at specific values. By default, `estat mfx` holds variables to their alternative-specific means. These marginal effects and predicted probabilities from the CL analyses were saved in Tables C.1 through C.3 in Appendix C. The interpretation of marginal effects is the marginal change in the probability of selecting each alternative for an increase in the number of that specific childcare alternative. As shown on the first line in Tables C.1 through C.3, the marginal effects of one-unit increase in the number of centers for the average child living in an average community was .0012**, 0.002**, and 0.007** for the 5-mile, 10-mile, and 25-minute models, respectively, and these marginal effects, though small, were statistically significant at the .01 level.

A.5.3 Discrete change of predicted probabilities

Similar to the marginal effects, one can also predict the probabilities of choosing each childcare option by changing the value of one variable while keeping all other variables the same. Predicted probabilities based on a few sets of specific values were reported in Table 5.4. As with `margins`, I used `at()` in the `estat mfx` command to change the values of the independent variables. This produced predictions and marginal effects with the values specified. This is referred to as the discrete change in Long (2016), and summarized in the equation below:

$$DC(x_k) = \frac{\Delta\pi(x)}{\Delta x_k(start \to end)} = \pi(x_k = end, x = x^*) - \pi(x_k = start, x = x^*)$$

APPENDIX B ESTIMATED COEFFICIENT OUTPUTS BY BUFFER SIZE

Table B. 1 Stata outputs of estimated coefficients: 5-mile model

```
Alternative-specific conditional logit         Number of obs      =     42,636
Case variable: childid                         Number of cases    =       7106

Alternative variable: cc_options               Alts per case: min =          6
                                                              avg =        6.0
                                                              max =          6

                                                  Wald chi2(376)  =    2875.22
Log likelihood = -10008.658                       Prob > chi2     =     0.0000

------------------------------------------------------------------------------------------
                  choice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------------+----------------------------------------------------------------
cc_options               |
                     num |   .0496719   .0055421     8.96   0.000     .0388096    .0605342
-------------------------+----------------------------------------------------------------
center                   |
             p_immigrant |  -.4714512   .1393693    -3.38   0.001    -.7446101   -.1982923
        avg_pct_5_yrs_mi |   .0010162    .004821     0.21   0.833    -.0084328    .0104652
      avg_pct_foreign_mi |  -.0023798   .0007643    -3.11   0.002    -.0038778   -.0008818
      avg_pct_ratio_1_mi |   -.001237   .0015363    -0.81   0.421    -.0042481    .0017741
avg_pct_female_labor_mi  |  -.0015312   .0029551    -0.52   0.604    -.0073231    .0042607
                  medinc |   .0115801   .0059447     1.95   0.051    -.0000713    .0232316
               c_citizen |   .6481803   .3068992     2.11   0.035     .0466689    1.249692
                 c_white |   .1036007   .1687221     0.61   0.539    -.2270885    .4342899
                 c_black |  -.0599917   .2101297    -0.29   0.775    -.4718384    .3518549
              c_hispanic |  -.0257112   .1996184    -0.13   0.898    -.4169561    .3655337
                 c_asian |   .3749281   .2606447     1.44   0.150    -.1359262    .8857825
                f_income |   .4429438   .0559137     7.92   0.000      .333355    .5525326
                   p_edu |    .453297   .0622462     7.28   0.000     .3312966    .5752973
                f_single |   .3461465   .1206066     2.87   0.004     .1097619    .5825312
                  f_size |  -.2271436   .0643326    -3.53   0.000    -.3532331   -.1010541
                language |  -.3961922    .187549    -2.11   0.035    -.7637816   -.0286028
              c_siblings |   -.077861    .072485    -1.07   0.283     -.219929    .0642069
         f_below_poverty |  -.0920809   .1468175    -0.63   0.531     -.379838    .1956762
                  f_food |   .0107095   .1040267     0.10   0.918     -.193179    .2145981
           f_wic_pregnant|  -.1849397   .1621829    -1.14   0.254    -.5028123     .132933
             f_wic_child |   .0081261   .1637376     0.05   0.960    -.3127938    .3290459
             f_food_stamp|   -.051678    .180911    -0.29   0.775    -.4062569     .302901
             f_religious |   .1980285   .0818573     2.42   0.016     .0375912    .3584659
        m_age_firstbirth |   .0249036   .0090122     2.76   0.006       .00724    .0425673
         m_married_birth |   .1295355   .1134429     1.14   0.254    -.0928085    .3518796
                         |
                f_region |
                Midwest  |  -.6739841   .6487107    -1.04   0.299    -1.945434    .5974654
                  South  |  -1.213134   .6391548    -1.90   0.058    -2.465854    .0395867
                   West  |  -2.065402   .6202382    -3.33   0.001    -3.281046   -.8497572
                         |
                f_locale |
                 suburb  |   .1684381   .1238755     1.36   0.174    -.0743534    .4112297
                   town  |  -.0898018   .1896205    -0.47   0.636    -.4614512    .2818476
                  rural  |  -.2213925    .140061    -1.58   0.114     -.495907    .0531219
                         |
              c_age_prek |  -.0005935   .0087107    -0.07   0.946     -.017666    .0164791
                c_female |   -.044181   .0768755    -0.57   0.565    -.1948543    .1064923
              c_lowbirth |  -.0138753   .1603408    -0.09   0.931    -.3281376    .3003869
               c_preterm |   .1336377   .1078563     1.24   0.215    -.0777568    .3450323
             c_breastfed |   .2396799   .0907023     2.64   0.008     .0619066    .4174531
                c_iep_pk |  -.6933437   .2576766    -2.69   0.007    -1.198381   -.1883067
                  c_twin |   .2028166   .7507211     0.27   0.787     -1.26857    1.674203
             c_birth_cpl |  -.0768555   .1161284    -0.66   0.508    -.3044629     .150752
         c_first_word_15 |  -.1427097   .0956487    -1.49   0.136    -.3301776    .0447583
         c_first_step_15 |   -.296687   .1580211    -1.88   0.060    -.6064027    .0130287
                         |
                   state |
```

4	.4800488	.3440259	1.40	0.163	-.1942296	1.154327
5	-1.49682	.6267169	-2.39	0.017	-2.725163	-.2684774
8	.195559	.4282343	0.46	0.648	-.6437648	1.034883
9	-.8973275	.6245323	-1.44	0.151	-2.121388	.3267333
12	-.01653	.3951489	-0.04	0.967	-.7910076	.7579477
13	-.8265439	.3995734	-2.07	0.039	-1.609693	-.0433944
15	1.597099	.802649	1.99	0.047	.0239356	3.170262
17	-.0540304	.429825	-0.13	0.900	-.896472	.7884112
18	-.4765343	.4272904	-1.12	0.265	-1.314008	.3609395
19	-.3597806	.7189359	-0.50	0.617	-1.768869	1.049308
20	-.5026294	.4728842	-1.06	0.288	-1.429466	.4242066
22	-.7628732	.6592157	-1.16	0.247	-2.054912	.5291658
24	-.8143491	.3815683	-2.13	0.033	-1.562209	-.0664891
25	-2.037214	.8458731	-2.41	0.016	-3.695095	-.3793332
27	-.3732126	.3875542	-0.96	0.336	-1.132805	.3863797
28	-.2219175	.3434596	-0.65	0.518	-.895086	.451251
29	-.5703182	.4027232	-1.42	0.157	-1.359641	.2190048
30	.4047352	.3293969	1.23	0.219	-.2408709	1.050341
31	-.5014059	.4354542	-1.15	0.250	-1.35488	.3520686
32	.9105771	.3578416	2.54	0.011	.2092204	1.611934
33	-.8870434	.6490437	-1.37	0.172	-2.159146	.3850588
34	-2.432454	.6198804	-3.92	0.000	-3.647397	-1.217511
35	-.4435293	.4220656	-1.05	0.293	-1.270763	.3837041
36	-.7963118	.6267905	-1.27	0.204	-2.024799	.432175
37	-.0242598	.3684075	-0.07	0.947	-.7463252	.6978056
39	-.8482628	.354105	-2.40	0.017	-1.542296	-.1542297
40	-1.068667	.4641496	-2.30	0.021	-1.978383	-.15895
42	-1.689969	.607663	-2.78	0.005	-2.880966	-.4989713
45	-.0830396	.3445732	-0.24	0.810	-.7583907	.5923115
47	.140229	.347977	0.40	0.687	-.5417934	.8222515
48	-.0077567	.314135	-0.02	0.980	-.62345	.6079366
49	-.0644325	.3178138	-0.20	0.839	-.6873362	.5584712
50	0	(omitted)				
51	-.2358964	.3667573	-0.64	0.520	-.9547275	.4829348
53	0	(omitted)				
54	-.0562464	.387095	-0.15	0.884	-.8149386	.7024459
55	0	(omitted)				
_cons	-.9598628	1.278743	-0.75	0.453	-3.466153	1.546428
head_start						
p_immigrant	.0187623	.1926182	0.10	0.922	-.3587625	.3962871
avg_pct_5_yrs_mi	-.0140547	.0063427	-2.22	0.027	-.0264861	-.0016233
avg_pct_foreign_mi	.0004105	.000945	0.43	0.664	-.0014417	.0022628
avg_pct_ratio_1_mi	-.0007175	.0019971	-0.36	0.719	-.0046318	.0031967
avg_pct_female_labor_mi	-.0070107	.0039856	-1.76	0.079	-.0148223	.000801
medinc	-.0121449	.009107	-1.33	0.182	-.0299942	.0057044
c_citizen	.2611237	.4343146	0.60	0.548	-.5901174	1.112365
c_white	.1825959	.24087	0.76	0.448	-.2895007	.6546925
c_black	.8685672	.2659372	3.27	0.001	.3473398	1.389795
c_hispanic	.6369304	.2701765	2.36	0.018	.1073942	1.166467
c_asian	-.022048	.4291874	-0.05	0.959	-.8632398	.8191439
f_income	.1075597	.0818134	1.31	0.189	-.0527915	.267911
p_edu	.2864756	.092746	3.09	0.002	.1046967	.4682544
f_single	.6262256	.1362006	4.60	0.000	.3592772	.8931739
f_size	-.025201	.0607509	-0.41	0.678	-.1442706	.0938686
language	-.1530198	.2274376	-0.67	0.501	-.5987893	.2927496
c_siblings	-.1914417	.0732844	-2.61	0.009	-.3350764	-.047807
f_below_poverty	.3583544	.1622128	2.21	0.027	.0404233	.6762856
f_food	.0096019	.1122705	0.09	0.932	-.2104443	.2296481
f_wic_pregnant	.1420752	.1959586	0.73	0.468	-.2419966	.5261469
f_wic_child	.6155152	.2119329	2.90	0.004	.2001343	1.030896
f_food_stamp	-.0819091	.2024108	-0.40	0.686	-.478627	.3148088
f_religious	.2621527	.1101929	2.38	0.017	.0461786	.4781268
m_age_firstbirth	-.0075632	.0127029	-0.60	0.552	-.0324603	.017334
m_married_birth	-.1937054	.1339763	-1.45	0.148	-.4562941	.0688834
f_region						
Midwest	-.8776326	.8682365	-1.01	0.312	-2.579345	.8240796
South	-1.494862	.8169155	-1.83	0.067	-3.095987	.1062626
West	-1.152943	.7912708	-1.46	0.145	-2.703805	.397919

```
                         |
                f_locale |
                 suburb  |   .1824582   .1734209     1.05   0.293    -.1574406     .522357
                   town  |   .2567893   .2516344     1.02   0.307     -.236405    .7499836
                  rural  |   .1966353   .1952502     1.01   0.314    -.1860481    .5793188
                         |
              c_age_prek |   .0080446   .0119822     0.67   0.502    -.0154401    .0315293
                c_female |  -.0803749   .1042418    -0.77   0.441    -.2846851    .1239352
              c_lowbirth |   .1877428   .1981379     0.95   0.343    -.2006004     .576086
               c_preterm |   .0829095   .1436137     0.58   0.564    -.1985681    .3643872
             c_breastfed |   .0859733   .1169848     0.73   0.462    -.1433128    .3152594
                c_iep_pk |   .4483041   .2570982     1.74   0.081    -.0555992    .9522073
                  c_twin |   .4389181   .9788055     0.45   0.654    -1.479505    2.357342
             c_birth_cpl |   .0195974   .1528132     0.13   0.898    -.2799111    .3191058
         c_first_word_15 |  -.0279961   .1306362    -0.21   0.830    -.2840382    .2280461
         c_first_step_15 |  -.2516946   .2083364    -1.21   0.227    -.6600264    .1566372
                         |
                   state |
                      4  |  -.4239177   .4734858    -0.90   0.371    -1.351933    .5040974
                      5  |   .1461878   .5403079     0.27   0.787    -.9127962    1.205172
                      8  |    .708112   .5787242     1.22   0.221    -.4261666    1.842391
                      9  |  -.3323073   .8146797    -0.41   0.683     -1.92905    1.264436
                     12  |   .7224739   .5155808     1.40   0.161     -.288046    1.732994
                     13  |   .6554119   .4750609     1.38   0.168    -.2756903    1.586514
                     15  |   1.098072   1.294261     0.85   0.396    -1.438633    3.634778
                     17  |   .8956838   .5864361     1.53   0.127    -.2537098    2.045077
                     18  |  -.1898541   .7041188    -0.27   0.787    -1.569902    1.190193
                     19  |   .7506066    .932042     0.81   0.421    -1.076162    2.577375
                     20  |   .4842504   .5901162     0.82   0.412    -.6723562    1.640857
                     22  |   .0645307   .6778398     0.10   0.924    -1.264011    1.393072
                     24  |   .2598849   .5734559     0.45   0.650     -.864068    1.383838
                     25  |  -.4165409   1.025668    -0.41   0.685    -2.426813    1.593731
                     27  |   1.076932   .5707614     1.89   0.059    -.0417393    2.195604
                     28  |   .7578129   .4099874     1.85   0.065    -.0457477    1.561373
                     29  |  -.0104134   .6504718    -0.02   0.987    -1.285315    1.264488
                     30  |   -.188719     .45096    -0.42   0.676    -1.072584    .6951463
                     31  |   .9578847   .6291298     1.52   0.128     -.275187    2.190956
                     32  |  -1.163129    .626279    -1.86   0.063    -2.390613    .0643556
                     33  |  -.3209656     .85702    -0.37   0.708    -2.000694    1.358763
                     34  |  -1.632267   .8547856    -1.91   0.056    -3.307616     .043082
                     35  |   -.435225   .6546917    -0.66   0.506    -1.718397    .8479471
                     36  |   .3689256   .7856324     0.47   0.639    -1.170886    1.908737
                     37  |   .8158543   .4564509     1.79   0.074     -.078773    1.710482
                     39  |   -.369798   .5675847    -0.65   0.515    -1.482244    .7426475
                     40  |   .1622638   .5666108     0.29   0.775     -.948273    1.272801
                     42  |  -.4061235   .7597988    -0.53   0.593    -1.895302    1.083055
                     45  |   -.388976   .4983017    -0.78   0.435    -1.365629    .5876774
                     47  |   .1269015   .4740533     0.27   0.789    -.8022258    1.056029
                     48  |  -.2539893   .4351659    -0.58   0.559    -1.106899    .5989202
                     49  |  -.0522113   .4684001    -0.11   0.911    -.9702585     .865836
                     50  |          0  (omitted)
                     51  |   .4994102   .4898504     1.02   0.308    -.4606789    1.459499
                     53  |          0  (omitted)
                     54  |   1.590007   .4906788     3.24   0.001     .6282947     2.55172
                     55  |          0  (omitted)
                         |
                   _cons |   .8603948   1.690148     0.51   0.611    -2.452234    4.173024
-------------------------+----------------------------------------------------------------
non_relative             |
             p_immigrant |  -.3690091   .2223862    -1.66   0.097    -.8048781      .06686
       avg_pct_5_yrs_mi |  -.0089488   .0076546    -1.17   0.242    -.0239515    .0060539
     avg_pct_foreign_mi |   -.001253   .0012967    -0.97   0.334    -.0037946    .0012886
     avg_pct_ratio_1_mi |  -.0037023   .0024063    -1.54   0.124    -.0084185    .0010139
avg_pct_female_labor_mi |   .0018246   .0043725     0.42   0.676    -.0067454    .0103946
                  medinc |  -.0092434    .009346    -0.99   0.323    -.0275612    .0090744
               c_citizen |   .3662553   .5686982     0.64   0.520    -.7483727    1.480883
                 c_white |   .9429953   .3179598     2.97   0.003     .3198056    1.566185
                 c_black |   .7108109    .397009     1.79   0.073    -.0673124    1.488934
              c_hispanic |   1.155026   .3553982     3.25   0.001     .4584582    1.851594
                 c_asian |  -.5065372   .6333786    -0.80   0.424    -1.747937    .7348621
                f_income |   .4788981   .0816711     5.86   0.000     .3188257    .6389706
```

p_edu	.4650865	.088497	5.26	0.000	.2916356	.6385374
f_single	.4579523	.1809871	2.53	0.011	.1032242	.8126804
f_size	-.176424	.1059528	-1.67	0.096	-.3840876	.0312396
language	-.2696653	.342782	-0.79	0.431	-.9415056	.4021751
c_siblings	-.2101932	.1174605	-1.79	0.074	-.4404116	.0200251
f_below_poverty	-.1581975	.2382979	-0.66	0.507	-.6252528	.3088579
f_food	.183686	.1550246	1.18	0.236	-.1201567	.4875286
f_wic_pregnant	.0503788	.2367206	0.21	0.831	-.4135851	.5143426
f_wic_child	-.1775717	.2367691	-0.75	0.453	-.6416307	.2864873
f_food_stamp	.23517	.2539525	0.93	0.354	-.2625678	.7329077
f_religious	.0197319	.119812	0.16	0.869	-.2150954	.2545591
m_age_firstbirth	.0040755	.0132286	0.31	0.758	-.021852	.0300031
m_married_birth	.022977	.1719615	0.13	0.894	-.3140613	.3600154
f_region						
Midwest	-.9804156	.7907611	-1.24	0.215	-2.530279	.5694477
South	-2.873158	1.00436	-2.86	0.004	-4.841667	-.9046482
West	-1.798127	.7482555	-2.40	0.016	-3.26468	-.331573
f_locale						
suburb	-.1210885	.1940587	-0.62	0.533	-.5014365	.2592595
town	-.0823142	.2577987	-0.32	0.750	-.5875904	.4229621
rural	-.1006437	.2149589	-0.47	0.640	-.5219554	.3206679
c_age_prek	-.0087179	.0129153	-0.68	0.500	-.0340314	.0165956
c_female	.0244198	.1113599	0.22	0.826	-.1938416	.2426811
c_lowbirth	-.1856893	.2376535	-0.78	0.435	-.6514816	.280103
c_preterm	.4084408	.1512182	2.70	0.007	.1120586	.704823
c_breastfed	.2574717	.1360862	1.89	0.058	-.0092523	.5241958
c_iep_pk	-.3896455	.3343952	-1.17	0.244	-1.045048	.2657571
c_twin	-.1156404	1.259833	-0.09	0.927	-2.584868	2.353587
c_birth_cpl	.1111696	.1602562	0.69	0.488	-.2029268	.4252659
c_first_word_15	-.0022164	.136627	-0.02	0.987	-.2700004	.2655676
c_first_step_15	-.1208502	.2272351	-0.53	0.595	-.5662228	.3245224
state						
4	.3928953	.5039661	0.78	0.436	-.5948601	1.380651
5	-.3124201	1.277745	-0.24	0.807	-2.816754	2.191914
8	-.043158	.6464565	-0.07	0.947	-1.310189	1.223873
9	-1.945288	.7960679	-2.44	0.015	-3.505552	-.3850235
12	-.1977497	1.00945	-0.20	0.845	-2.176235	1.780736
13	.3923145	.9703048	0.40	0.686	-1.509448	2.294077
15	.3664847	1.303605	0.28	0.779	-2.188534	2.921503
17	1.258429	.5354104	2.35	0.019	.2090443	2.307815
18	-.0536404	.5973227	-0.09	0.928	-1.224371	1.117091
19	1.85026	.7386976	2.50	0.012	.4024395	3.298081
20	.3871759	.6303582	0.61	0.539	-.8483035	1.622655
22	1.134609	1.102956	1.03	0.304	-1.027146	3.296364
24	1.506439	.8331565	1.81	0.071	-.1265181	3.139395
25	-2.911214	1.317311	-2.21	0.027	-5.493096	-.3293311
27	1.461526	.5089855	2.87	0.004	.4639327	2.459119
28	.2312487	.8857866	0.26	0.794	-1.504861	1.967358
29	-.8263831	.612251	-1.35	0.177	-2.026373	.3736068
30	.0762057	.4676046	0.16	0.871	-.8402825	.9926939
31	-.7824051	.6583048	-1.19	0.235	-2.072659	.5078486
32	.0104837	.5760858	0.02	0.985	-1.118624	1.139591
33	-2.49305	.9349056	-2.67	0.008	-4.325432	-.6606688
34	-2.508052	.7894919	-3.18	0.001	-4.055428	-.9606767
35	-.3197355	.6410391	-0.50	0.618	-1.576149	.9366781
36	-.3978335	.7406261	-0.54	0.591	-1.849434	1.053767
37	-.4014707	1.048961	-0.38	0.702	-2.457396	1.654455
39	-.2755686	.4916303	-0.56	0.575	-1.239146	.6880091
40	.2816259	1.060298	0.27	0.791	-1.79652	2.359772
42	-1.798512	.7373168	-2.44	0.015	-3.243627	-.3533978
45	.8400929	.8287276	1.01	0.311	-.7841832	2.464369
47	.3304111	.8920163	0.37	0.711	-1.417909	2.078731
48	.9151806	.7909855	1.16	0.247	-.6351224	2.465484
49	1.796532	.3909763	4.59	0.000	1.030233	2.562832
50	0	(omitted)				
51	1.240289	.8411727	1.47	0.140	-.4083788	2.888957
53	0	(omitted)				

54	1.324494	.8468424	1.56	0.118	-.3352864	2.984275
55	0	(omitted)				
_cons	-.862974	1.874536	-0.46	0.645	-4.536997	2.811049
parental	(base alternative)					
relative						
p_immigrant	-.1242246	.1609328	-0.77	0.440	-.439647	.1911978
avg_pct_5_yrs_mi	.0038381	.0054017	0.71	0.477	-.0067491	.0144254
avg_pct_foreign_mi	-.000752	.0008401	-0.90	0.371	-.0023985	.0008946
avg_pct_ratio_1_mi	-.0009871	.0017028	-0.58	0.562	-.0043244	.0023503
avg_pct_female_labor_mi	-.0021725	.0033966	-0.64	0.522	-.0088296	.0044847
medinc	-.0082974	.007092	-1.17	0.242	-.0221975	.0056028
c_citizen	.7369331	.3957161	1.86	0.063	-.0386561	1.512522
c_white	.1321577	.1978356	0.67	0.504	-.255593	.5199084
c_black	.1624153	.2368277	0.69	0.493	-.3017586	.6265891
c_hispanic	.3630012	.2256829	1.61	0.108	-.0793293	.8053316
c_asian	.2763395	.3111646	0.89	0.374	-.333532	.886211
f_income	.309775	.0647801	4.78	0.000	.1828083	.4367418
p_edu	.1294113	.0755663	1.71	0.087	-.018696	.2775185
f_single	1.098728	.1218539	9.02	0.000	.8598984	1.337557
f_size	.1534888	.0507509	3.02	0.002	.0540189	.2529587
language	-.035239	.1954216	-0.18	0.857	-.4182582	.3477803
c_siblings	-.376854	.0628378	-6.00	0.000	-.5000138	-.2536942
f_below_poverty	-.1868305	.1482998	-1.26	0.208	-.4774928	.1038318
f_food	.1067428	.1027674	1.04	0.299	-.0946776	.3081631
f_wic_pregnant	.1578828	.1800362	0.88	0.381	-.1949817	.5107472
f_wic_child	-.096833	.184892	-0.52	0.600	-.4592147	.2655487
f_food_stamp	.098517	.1818909	0.54	0.588	-.2579826	.4550165
f_religious	.0053429	.0936872	0.06	0.955	-.1782806	.1889665
m_age_firstbirth	-.008965	.0106472	-0.84	0.400	-.0298331	.011903
m_married_birth	.1815577	.1202828	1.51	0.131	-.0541922	.4173077
f_region						
Midwest	.1992354	.8025083	0.25	0.804	-1.373652	1.772123
South	-1.217303	.8161426	-1.49	0.136	-2.816913	.3823075
West	-1.453684	.7908211	-1.84	0.066	-3.003665	.0962966
f_locale						
suburb	.2441416	.1441986	1.69	0.090	-.0384825	.5267657
town	.2122758	.2211366	0.96	0.337	-.221144	.6456956
rural	.1764705	.1632879	1.08	0.280	-.143568	.4965089
c_age_prek	.0040576	.0100641	0.40	0.687	-.0156677	.023783
c_female	.018056	.0889369	0.20	0.839	-.156257	.1923691
c_lowbirth	.1436643	.178219	0.81	0.420	-.2056385	.4929672
c_preterm	.0439177	.1250199	0.35	0.725	-.2011168	.2889522
c_breastfed	-.0551817	.1003533	-0.55	0.582	-.2518705	.1415071
c_iep_pk	-.1379573	.2545938	-0.54	0.588	-.6369519	.3610373
c_twin	.2356447	.9437377	0.25	0.803	-1.614047	2.085337
c_birth_cpl	-.0346763	.1330591	-0.26	0.794	-.2954673	.2261146
c_first_word_15	.0045972	.1084528	0.04	0.966	-.2079663	.2171607
c_first_step_15	.0333851	.1696314	0.20	0.844	-.2990863	.3658565
state						
4	1.213517	.4113628	2.95	0.003	.4072607	2.019773
5	.8779117	.5139738	1.71	0.088	-.1294583	1.885282
8	1.566876	.5033561	3.11	0.002	.5803165	2.553436
9	.2352104	.7774911	0.30	0.762	-1.288644	1.759065
12	.9502181	.5076023	1.87	0.061	-.0446641	1.9451
13	1.029461	.474482	2.17	0.030	.0994929	1.959428
15	1.766201	.9944469	1.78	0.076	-.1828793	3.715281
17	.2546643	.4833346	0.53	0.598	-.6926541	1.201983
18	-.3104316	.5024001	-0.62	0.537	-1.295118	.6742546
19	.2100406	.7467903	0.28	0.779	-1.253641	1.673723
20	-.2850192	.499487	-0.57	0.568	-1.263996	.6939574
22	.5596438	.6562689	0.85	0.394	-.7266195	1.845907
24	.7260026	.4903047	1.48	0.139	-.2349769	1.686982
25	.1981686	.9654016	0.21	0.837	-1.693984	2.090321
27	-.2953253	.4565722	-0.65	0.518	-1.19019	.5995397

28	.5296789	.4412032	1.20	0.230	-.3350634	1.394421
29	-.6795524	.5038191	-1.35	0.177	-1.66702	.3079149
30	.6765591	.4257551	1.59	0.112	-.1579055	1.511024
31	-.4316479	.5308381	-0.81	0.416	-1.472072	.6087757
32	1.272232	.4285387	2.97	0.003	.4323116	2.112153
33	-.4321258	.8310986	-0.52	0.603	-2.061049	1.196798
34	-.5872326	.7744911	-0.76	0.448	-2.105207	.930742
35	.2694114	.5145369	0.52	0.601	-.7390624	1.277885
36	.862141	.766455	1.12	0.261	-.6400833	2.364365
37	.8791342	.4694879	1.87	0.061	-.0410452	1.799313
39	-.2488939	.4118099	-0.60	0.546	-1.056026	.5582386
40	.1892196	.5393144	0.35	0.726	-.8678173	1.246257
42	-.4976014	.7556086	-0.66	0.510	-1.978567	.9833643
45	1.010902	.4381573	2.31	0.021	.1521295	1.869675
47	.678778	.4575229	1.48	0.138	-.2179504	1.575506
48	.2929803	.4247756	0.69	0.490	-.5395646	1.125525
49	.7082218	.4190957	1.69	0.091	-.1131907	1.529634
50	0	(omitted)				
51	.4676682	.4805119	0.97	0.330	-.4741177	1.409454
53	0	(omitted)				
54	1.442734	.4827132	2.99	0.003	.4966334	2.388834
55	0	(omitted)				
_cons	-1.848785	1.501164	-1.23	0.218	-4.791012	1.093442
state_pre_K						
p_immigrant	-.2127844	.1408042	-1.51	0.131	-.4887556	.0631867
avg_pct_5_yrs_mi	.0026183	.0046733	0.56	0.575	-.0065411	.0117777
avg_pct_foreign_mi	-.0035178	.0007217	-4.87	0.000	-.0049322	-.0021033
avg_pct_ratio_1_mi	.0017099	.0015017	1.14	0.255	-.0012334	.0046532
avg_pct_female_labor_mi	.0007168	.0029782	0.24	0.810	-.0051204	.0065541
medinc	.0033613	.0063424	0.53	0.596	-.0090695	.0157922
c_citizen	.6950058	.3286875	2.11	0.034	.0507901	1.339221
c_white	-.0103634	.1731538	-0.06	0.952	-.3497385	.3290118
c_black	.2479852	.2067209	1.20	0.230	-.1571802	.6531507
c_hispanic	.289505	.1981162	1.46	0.144	-.0987957	.6778057
c_asian	.2777179	.2754842	1.01	0.313	-.2622212	.817657
f_income	.1984759	.0594521	3.34	0.001	.081952	.3149998
p_edu	.3085087	.0674817	4.57	0.000	.176247	.4407704
f_single	.3054248	.1141631	2.68	0.007	.0816693	.5291803
f_size	-.0718053	.0531473	-1.35	0.177	-.1759722	.0323616
language	-.0259448	.1672764	-0.16	0.877	-.3538005	.3019109
c_siblings	-.1158254	.0614786	-1.88	0.060	-.2363213	.0046706
f_below_poverty	.0632785	.1306487	0.48	0.628	-.1927883	.3193452
f_food	-.0514871	.0934221	-0.55	0.582	-.2345911	.1316169
f_wic_pregnant	-.1386519	.1522912	-0.91	0.363	-.4371372	.1598334
f_wic_child	.6457961	.1605019	4.02	0.000	.3312183	.960374
f_food_stamp	-.0215352	.1678088	-0.13	0.898	-.3504345	.3073641
f_religious	.1754132	.0843591	2.08	0.038	.0100724	.3407539
m_age_firstbirth	-.0023679	.0095545	-0.25	0.804	-.0210944	.0163587
m_married_birth	.0617351	.1064381	0.58	0.562	-.1468799	.27035
f_region						
Midwest	-.2275835	.6466632	-0.35	0.725	-1.49502	1.039853
South	-2.865225	.7195174	-3.98	0.000	-4.275453	-1.454997
West	-2.149412	.6384488	-3.37	0.001	-3.400748	-.8980752
f_locale						
suburb	-.0448872	.1245112	-0.36	0.718	-.2889247	.1991504
town	.0949583	.1915528	0.50	0.620	-.2804783	.4703949
rural	-.014405	.1403053	-0.10	0.918	-.2893982	.2605883
c_age_prek	.0223334	.0089995	2.48	0.013	.0046947	.0399722
c_female	-.1331913	.0798704	-1.67	0.095	-.2897344	.0233518
c_lowbirth	-.0898613	.1620237	-0.55	0.579	-.407422	.2276993
c_preterm	.1974008	.1098337	1.80	0.072	-.0178692	.4126709
c_breastfed	.1162795	.091265	1.27	0.203	-.0625965	.2951556
c_iep_pk	.6373128	.2070984	3.08	0.002	.2314074	1.043218
c_twin	.0722006	.8600085	0.08	0.933	-1.613385	1.757786
c_birth_cpl	.0937885	.1173489	0.80	0.424	-.1362111	.3237882
c_first_word_15	.0329427	.0962445	0.34	0.732	-.1556931	.2215785

c_first_step_15	.0527326	.1493229	0.35	0.724	-.2399349	.3454001
state						
4	1.081241	.3600908	3.00	0.003	.3754759	1.787006
5	2.186215	.514155	4.25	0.000	1.178489	3.19394
8	1.022489	.4780431	2.14	0.032	.0855413	1.959436
9	-.6352217	.6346747	-1.00	0.317	-1.879161	.6087179
12	3.556791	.5044543	7.05	0.000	2.568078	4.545503
13	2.521144	.4880544	5.17	0.000	1.564575	3.477714
15	-12.79715	658.0852	-0.02	0.984	-1302.62	1277.026
17	.1968617	.4121951	0.48	0.633	-.6110259	1.004749
18	-1.869198	.5100507	-3.66	0.000	-2.868879	-.8695166
19	1.008141	.6297253	1.60	0.109	-.226098	2.24238
20	-1.084816	.4527418	-2.40	0.017	-1.972174	-.1974585
22	.2913773	.7935964	0.37	0.713	-1.264043	1.846798
24	1.26385	.5189958	2.44	0.015	.246637	2.281063
25	-1.451977	.9002032	-1.61	0.107	-3.216342	.3123892
27	-.8033459	.3910353	-2.05	0.040	-1.569761	-.0369308
28	.3830696	.4932607	0.78	0.437	-.5837036	1.349843
29	-.7084462	.4169703	-1.70	0.089	-1.525693	.1088007
30	-.3459057	.4078664	-0.85	0.396	-1.145309	.4534977
31	-1.866031	.5301194	-3.52	0.000	-2.905046	-.8270157
32	.1768216	.4223508	0.42	0.675	-.6509708	1.004614
33	-2.936461	.8548734	-3.43	0.001	-4.611982	-1.26094
34	-1.198728	.6275075	-1.91	0.056	-2.42862	.0311642
35	-.0051681	.4582881	-0.01	0.991	-.9033962	.89306
36	.0350066	.6266607	0.06	0.955	-1.193226	1.263239
37	1.094041	.5158021	2.12	0.034	.083087	2.104994
39	-1.420135	.3698666	-3.84	0.000	-2.14506	-.6952097
40	1.704638	.5118528	3.33	0.001	.7014244	2.707851
42	-1.526939	.6111496	-2.50	0.012	-2.724771	-.3291082
45	.805445	.4963224	1.62	0.105	-.167329	1.778219
47	1.252864	.4861993	2.58	0.010	.2999305	2.205797
48	1.857095	.4549895	4.08	0.000	.9653318	2.748858
49	.6766086	.3582399	1.89	0.059	-.0255287	1.378746
50	0	(omitted)				
51	1.371052	.5067049	2.71	0.007	.3779288	2.364176
53	0	(omitted)				
54	2.315521	.5100294	4.54	0.000	1.315882	3.31516
55	0	(omitted)				
_cons	-2.356882	1.299504	-1.81	0.070	-4.903863	.1900992

Table B. 2 Stata outputs of estimated coefficients: 10-mile model

```
Alternative-specific conditional logit         Number of obs      =     42,636
Case variable: childid                         Number of cases    =       7106

Alternative variable: cc_options               Alts per case: min =          6
                                                              avg =        6.0
                                                              max =          6

                                                  Wald chi2(376)  =    2862.79
Log likelihood = -10039.498                       Prob > chi2     =     0.0000
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
cc_options						
num	.0077306	.0018674	4.14	0.000	.0040704	.0113907
center						
p_immigrant	-.4634019	.1385739	-3.34	0.001	-.7350018	-.1918021
avg_pct_5_yrs_mi	-.0106004	.0063978	-1.66	0.098	-.0231398	.001939
avg_pct_foreign~i	-.0022314	.000933	-2.39	0.017	-.0040601	-.0004028
avg_pct_ratio_1~i	.0015238	.001979	0.77	0.441	-.002355	.0054026
avg_pct_female_~i	.0043524	.0036166	1.20	0.229	-.002736	.0114408
medinc	.0161877	.0076286	2.12	0.034	.0012358	.0311395
c_citizen	.6033817	.3041779	1.98	0.047	.007204	1.199559
c_white	.0929649	.168148	0.55	0.580	-.2365992	.4225289
c_black	-.0101573	.2086261	-0.05	0.961	-.419057	.3987423
c_hispanic	-.0414347	.1989547	-0.21	0.835	-.4313787	.3485092
c_asian	.3593708	.2586717	1.39	0.165	-.1476164	.8663581
f_income	.4390437	.0557147	7.88	0.000	.3298449	.5482426
p_edu	.4600024	.0621099	7.41	0.000	.3382693	.5817356
f_single	.3558397	.1198771	2.97	0.003	.1208849	.5907946
f_size	-.2166307	.0637367	-3.40	0.001	-.3415523	-.0917091
language	-.4294639	.1850533	-2.32	0.020	-.7921618	-.0667661
c_siblings	-.0806779	.0718802	-1.12	0.262	-.2215606	.0602048
f_below_poverty	-.0808201	.1453346	-0.56	0.578	-.3656706	.2040304
f_food	-.0014323	.1032951	-0.01	0.989	-.2038869	.2010224
f_wic_pregnant	-.1451582	.1617422	-0.90	0.369	-.4621671	.1718506
f_wic_child	-.0136878	.1631321	-0.08	0.933	-.3334207	.3060452
f_food_stamp	-.0370167	.1804804	-0.21	0.837	-.3907518	.3167184
f_religious	.1961899	.0816493	2.40	0.016	.0361602	.3562197
m_age_firstbirth	.0246434	.0089716	2.75	0.006	.0070593	.0422275
m_married_birth	.1259255	.1128547	1.12	0.264	-.0952657	.3471167
f_region						
Midwest	-.6844749	.6456418	-1.06	0.289	-1.94991	.5809598
South	-1.040632	.6381322	-1.63	0.103	-2.291348	.2100841
West	-2.022909	.6212118	-3.26	0.001	-3.240461	-.8053559
f_locale						
suburb	.1237794	.1209535	1.02	0.306	-.1132851	.3608438
town	-.123391	.1897494	-0.65	0.516	-.495293	.248511
rural	-.231629	.1384425	-1.67	0.094	-.5029713	.0397134
c_age_prek	.0004586	.0086845	0.05	0.958	-.0165626	.0174799
c_female	-.0461313	.0766636	-0.60	0.547	-.1963893	.1041266
c_lowbirth	-.0032507	.1593703	-0.02	0.984	-.3156107	.3091093
c_preterm	.1405125	.1076808	1.30	0.192	-.0705381	.351563
c_breastfed	.2376337	.0904529	2.63	0.009	.0603493	.414918
c_iep_pk	-.7170975	.2578092	-2.78	0.005	-1.222394	-.2118007
c_twin	.2552424	.7458723	0.34	0.732	-1.20664	1.717125
c_birth_cpl	-.0728343	.1158394	-0.63	0.530	-.2998753	.1542066
c_first_word_15	-.1594465	.095335	-1.67	0.094	-.3462996	.0274066
c_first_step_15	-.2817391	.1573188	-1.79	0.073	-.5900783	.0266
state						
4	.6429837	.3415169	1.88	0.060	-.0263771	1.312344
5	-1.509331	.6286067	-2.40	0.016	-2.741378	-.2772847
8	.2691686	.4366393	0.62	0.538	-.5866287	1.124966

9	-.8847796	.6250919	-1.42	0.157	-2.109937	.340378
12	.0585867	.4249036	0.14	0.890	-.7742091	.8913825
13	-.8852096	.3978281	-2.23	0.026	-1.664938	-.105481
15	1.970624	.8039681	2.45	0.014	.3948755	3.546373
17	.1389984	.4267346	0.33	0.745	-.6973861	.9753829
18	-.2890557	.4306752	-0.67	0.502	-1.133164	.5550522
19	-.3229592	.7218403	-0.45	0.655	-1.73774	1.091822
20	-.481178	.474706	-1.01	0.311	-1.411585	.4492287
22	-.8909335	.6597815	-1.35	0.177	-2.184081	.4022144
24	-.891874	.3838999	-2.32	0.020	-1.644304	-.1394441
25	-2.111669	.8418797	-2.51	0.012	-3.761723	-.4616153
27	-.3161131	.3937775	-0.80	0.422	-1.087903	.4556766
28	-.2357646	.3416546	-0.69	0.490	-.9053953	.433866
29	-.4283092	.4064443	-1.05	0.292	-1.224925	.368307
30	.4351289	.3425067	1.27	0.204	-.2361719	1.10643
31	-.3173051	.4424589	-0.72	0.473	-1.184509	.5498984
32	.827869	.3617626	2.29	0.022	.1188274	1.536911
33	-.9364382	.6510739	-1.44	0.150	-2.21252	.3396432
34	-2.214657	.6162691	-3.59	0.000	-3.422522	-1.006791
35	-.0451179	.4312286	-0.10	0.917	-.8903105	.8000747
36	-.5680516	.6244052	-0.91	0.363	-1.791863	.65576
37	-.1497806	.3685305	-0.41	0.684	-.8720871	.5725258
39	-.7193724	.3539474	-2.03	0.042	-1.413096	-.0256483
40	-1.058577	.4621139	-2.29	0.022	-1.964304	-.1528502
42	-1.256199	.6045112	-2.08	0.038	-2.441019	-.0713784
45	-.1790037	.342324	-0.52	0.601	-.8499463	.491939
47	-.1602351	.3404735	-0.47	0.638	-.8275509	.5070806
48	-.0422543	.3146909	-0.13	0.893	-.6590371	.5745284
49	-.084222	.3184332	-0.26	0.791	-.7083396	.5398957
50	0	(omitted)				
51	-.4948856	.3626891	-1.36	0.172	-1.205743	.215972
53	0	(omitted)				
54	-.1360538	.386678	-0.35	0.725	-.8939287	.6218211
55	0	(omitted)				
_cons	-2.257454	1.387585	-1.63	0.104	-4.977071	.4621623
head_start						
p_immigrant	-.0023735	.1925286	-0.01	0.990	-.3797226	.3749757
avg_pct_5_yrs_mi	-.0196465	.0085773	-2.29	0.022	-.0364576	-.0028353
avg_pct_foreign~i	.0003867	.001123	0.34	0.731	-.0018143	.0025878
avg_pct_ratio_1~i	.0011981	.0026048	0.46	0.646	-.0039072	.0063034
avg_pct_female_~i	-.0090894	.0048096	-1.89	0.059	-.0185161	.0003374
medinc	-.0062196	.0112825	-0.55	0.581	-.0283328	.0158936
c_citizen	.2844853	.4346698	0.65	0.513	-.5674518	1.136422
c_white	.1823634	.2408694	0.76	0.449	-.289732	.6544587
c_black	.8613573	.2658329	3.24	0.001	.3403344	1.38238
c_hispanic	.6291413	.2699011	2.33	0.020	.1001449	1.158138
c_asian	-.0242781	.4281287	-0.06	0.955	-.8633949	.8148387
f_income	.1049043	.0814523	1.29	0.198	-.0547392	.2645479
p_edu	.2801951	.0927422	3.02	0.003	.0984237	.4619665
f_single	.6311201	.136285	4.63	0.000	.3640064	.8982339
f_size	-.0241524	.0607389	-0.40	0.691	-.1431984	.0948936
language	-.1350435	.2264529	-0.60	0.551	-.578883	.308796
c_siblings	-.1926591	.0731118	-2.64	0.008	-.3359556	-.0493626
f_below_poverty	.3482902	.1620613	2.15	0.032	.030656	.6659245
f_food	.0090206	.1123068	0.08	0.936	-.2110967	.229138
f_wic_pregnant	.1363298	.1962098	0.69	0.487	-.2482343	.5208939
f_wic_child	.6202284	.2119843	2.93	0.003	.2047468	1.03571
f_food_stamp	-.0744126	.2024839	-0.37	0.713	-.4712737	.3224485
f_religious	.266731	.1102149	2.42	0.016	.0507138	.4827481
m_age_firstbirth	-.008437	.0127085	-0.66	0.507	-.0333453	.0164712
m_married_birth	-.1921062	.1339842	-1.43	0.152	-.4547104	.070498
f_region						
Midwest	-.8041023	.8642272	-0.93	0.352	-2.497957	.8897519
South	-1.364286	.8164484	-1.67	0.095	-2.964496	.2359233
West	-1.135336	.7933856	-1.43	0.152	-2.690344	.4196709
f_locale						
suburb	.1283265	.1701107	0.75	0.451	-.2050842	.4617372

town	.2645528	.2541225	1.04	0.298	-.2335181	.7626237
rural	.1553711	.1968997	0.79	0.430	-.2305452	.5412873
c_age_prek	.0083843	.0120041	0.70	0.485	-.0151433	.0319119
c_female	-.075937	.1042096	-0.73	0.466	-.280184	.1283099
c_lowbirth	.1958081	.1977678	0.99	0.322	-.1918097	.583426
c_preterm	.0794346	.1435413	0.55	0.580	-.2019012	.3607704
c_breastfed	.0859057	.1168028	0.74	0.462	-.1430235	.3148349
c_iep_pk	.451831	.2567527	1.76	0.078	-.0513949	.955057
c_twin	.449262	.9715806	0.46	0.644	-1.455001	2.353525
c_birth_cpl	.0329612	.1529399	0.22	0.829	-.2667956	.332718
c_first_word_15	-.0231253	.1304575	-0.18	0.859	-.2788173	.2325667
c_first_step_15	-.257983	.2080837	-1.24	0.215	-.6658195	.1498535
state						
4	-.3183056	.4678587	-0.68	0.496	-1.235292	.5986807
5	.1164402	.5453463	0.21	0.831	-.9524189	1.185299
8	.907202	.5930351	1.53	0.126	-.2551255	2.06953
9	-.2114819	.8160214	-0.26	0.796	-1.810855	1.387891
12	.6076681	.5530601	1.10	0.272	-.4763099	1.691646
13	.5595283	.4759251	1.18	0.240	-.3732678	1.492324
15	.927948	1.292611	0.72	0.473	-1.605522	3.461418
17	.9838207	.5847768	1.68	0.092	-.1623208	2.129962
18	-.1631765	.7105799	-0.23	0.818	-1.555887	1.229535
19	.8648402	.9361859	0.92	0.356	-.9700503	2.699731
20	.6074301	.5963177	1.02	0.308	-.561331	1.776191
22	-.0882289	.6809485	-0.13	0.897	-1.422863	1.246406
24	.2412902	.5859337	0.41	0.680	-.9071188	1.389699
25	-.2883635	1.019172	-0.28	0.777	-2.285904	1.709177
27	1.217478	.5785757	2.10	0.035	.0834908	2.351466
28	.7237873	.4103946	1.76	0.078	-.0805713	1.528146
29	.0365277	.6552003	0.06	0.956	-1.247641	1.320697
30	-.1490852	.4691755	-0.32	0.751	-1.068652	.7704819
31	1.141954	.6404231	1.78	0.075	-.1132522	2.39716
32	-1.020211	.6297803	-1.62	0.105	-2.254558	.2141357
33	-.1595796	.8594866	-0.19	0.853	-1.844142	1.524983
34	-1.585914	.8518557	-1.86	0.063	-3.25552	.0836929
35	-.436349	.6665296	-0.65	0.513	-1.742723	.8700249
36	.4423787	.7828693	0.57	0.572	-1.092017	1.976774
37	.7762562	.4581408	1.69	0.090	-.1216833	1.674196
39	-.3439736	.5699807	-0.60	0.546	-1.461115	.773168
40	.0487427	.5628066	0.09	0.931	-1.054338	1.151823
42	-.2746493	.7585786	-0.36	0.717	-1.761436	1.212137
45	-.4170909	.4982295	-0.84	0.403	-1.393603	.559421
47	.0696589	.4702926	0.15	0.882	-.8520977	.9914155
48	-.3534532	.4370646	-0.81	0.419	-1.210084	.5031778
49	.0043125	.469675	0.01	0.993	-.9162335	.9248585
50	0	(omitted)				
51	.4502691	.4915614	0.92	0.360	-.5131736	1.413712
53	0	(omitted)				
54	1.47181	.4912842	3.00	0.003	.5089111	2.43471
55	0	(omitted)				
_cons	1.009401	1.853142	0.54	0.586	-2.622691	4.641494
non_relative						
p_immigrant	-.3719228	.2219087	-1.68	0.094	-.8068559	.0630103
avg_pct_5_yrs_mi	-.0148954	.0100839	-1.48	0.140	-.0346595	.0048687
avg_pct_foreign~i	-.0010935	.0014794	-0.74	0.460	-.0039931	.0018061
avg_pct_ratio_1~i	-.0025096	.0030456	-0.82	0.410	-.008479	.0034597
avg_pct_female_~i	.0017204	.0053974	0.32	0.750	-.0088583	.012299
medinc	-.0070214	.0116301	-0.60	0.546	-.0298159	.015773
c_citizen	.3903009	.5697879	0.68	0.493	-.7264628	1.507065
c_white	.9506439	.3178025	2.99	0.003	.3277625	1.573525
c_black	.7151213	.3971628	1.80	0.072	-.0633035	1.493546
c_hispanic	1.137364	.3554067	3.20	0.001	.4407796	1.833948
c_asian	-.5273725	.6325766	-0.83	0.404	-1.7672	.7124548
f_income	.476944	.0815983	5.85	0.000	.3170142	.6368738
p_edu	.4756764	.0885629	5.37	0.000	.3020963	.6492564
f_single	.4566075	.1809679	2.52	0.012	.101917	.8112981
f_size	-.1738629	.1059917	-1.64	0.101	-.3816028	.0338769

language	-.29014	.3414454	-0.85	0.395	-.9593606	.3790807
c_siblings	-.2102082	.1173988	-1.79	0.073	-.4403056	.0198893
f_below_poverty	-.1743366	.2383013	-0.73	0.464	-.6413986	.2927254
f_food	.1800917	.1550043	1.16	0.245	-.1237111	.4838945
f_wic_pregnant	.0581371	.2376671	0.24	0.807	-.4076818	.523956
f_wic_child	-.1866083	.237389	-0.79	0.432	-.6518823	.2786656
f_food_stamp	.2396453	.2541776	0.94	0.346	-.2585337	.7378242
f_religious	.0265681	.1197774	0.22	0.824	-.2081913	.2613275
m_age_firstbirth	.0032226	.0132195	0.24	0.807	-.0226872	.0291323
m_married_birth	.0209769	.1720809	0.12	0.903	-.3162956	.3582493
f_region						
Midwest	-.9327092	.7882805	-1.18	0.237	-2.477711	.6122922
South	-2.850054	1.005534	-2.83	0.005	-4.820864	-.879243
West	-1.678943	.7515035	-2.23	0.025	-3.151862	-.2060229
f_locale						
suburb	-.0757304	.1901625	-0.40	0.690	-.4484421	.2969814
town	-.0675775	.2583295	-0.26	0.794	-.573894	.438739
rural	-.059989	.2127729	-0.28	0.778	-.4770162	.3570382
c_age_prek	-.0089443	.0129276	-0.69	0.489	-.034282	.0163934
c_female	.0269057	.1113921	0.24	0.809	-.1914188	.2452303
c_lowbirth	-.1965286	.2372315	-0.83	0.407	-.6614937	.2684366
c_preterm	.4151586	.1511203	2.75	0.006	.1189683	.7113489
c_breastfed	.2542021	.1360104	1.87	0.062	-.0123734	.5207775
c_iep_pk	-.3892039	.3340299	-1.17	0.244	-1.043891	.2654827
c_twin	-.1273677	1.261605	-0.10	0.920	-2.600067	2.345332
c_birth_cpl	.1124385	.1602405	0.70	0.483	-.2016271	.426504
c_first_word_15	-.0017578	.1365271	-0.01	0.990	-.2693459	.2658303
c_first_step_15	-.1178986	.2270828	-0.52	0.604	-.5629727	.3271755
state						
4	.2354485	.5021966	0.47	0.639	-.7488388	1.219736
5	-.3384543	1.280224	-0.26	0.791	-2.847646	2.170738
8	-.1039385	.6600144	-0.16	0.875	-1.397543	1.189666
9	-1.970162	.7985137	-2.47	0.014	-3.53522	-.4051035
12	-.2015893	1.036788	-0.19	0.846	-2.233657	1.830478
13	.3749089	.9701663	0.39	0.699	-1.526582	2.2764
15	.3329286	1.307522	0.25	0.799	-2.229768	2.895625
17	1.251791	.5348552	2.34	0.019	.2034938	2.300088
18	-.0254758	.6089459	-0.04	0.967	-1.218988	1.168036
19	1.859394	.7470494	2.49	0.013	.395204	3.323584
20	.3353652	.6377284	0.53	0.599	-.9145595	1.58529
22	1.071776	1.107317	0.97	0.333	-1.098526	3.242078
24	1.504975	.837686	1.80	0.072	-.1368593	3.14681
25	-2.92732	1.316029	-2.22	0.026	-5.506688	-.3479512
27	1.495669	.5239208	2.85	0.004	.4688027	2.522534
28	.2544292	.8863767	0.29	0.774	-1.482837	1.991696
29	-.8026237	.6210163	-1.29	0.196	-2.019793	.414546
30	-.0312955	.4886329	-0.06	0.949	-.9889984	.9264074
31	-.6768262	.6749894	-1.00	0.316	-1.999781	.6461286
32	-.1046929	.5816676	-0.18	0.857	-1.24474	1.035355
33	-2.491073	.9414876	-2.65	0.008	-4.336355	-.6457913
34	-2.462705	.7850551	-3.14	0.002	-4.001385	-.9240253
35	-.3311103	.6565762	-0.50	0.614	-1.617976	.9557554
36	-.3184939	.7383539	-0.43	0.666	-1.765641	1.128653
37	-.451139	1.049964	-0.43	0.667	-2.50903	1.606752
39	-.2864223	.4956355	-0.58	0.563	-1.25785	.6850055
40	.2166574	1.05984	0.20	0.838	-1.860591	2.293906
42	-1.67602	.7378598	-2.27	0.023	-3.122199	-.2298414
45	.8970087	.8295161	1.08	0.280	-.728813	2.52283
47	.296161	.8898504	0.33	0.739	-1.447914	2.040236
48	.9913314	.7937239	1.25	0.212	-.5643389	2.547002
49	1.728333	.3923499	4.41	0.000	.9593411	2.497324
50	0	(omitted)				
51	1.177465	.839301	1.40	0.161	-.4675347	2.822465
53	0	(omitted)				
54	1.319149	.848582	1.55	0.120	-.3440409	2.982339
55	0	(omitted)				

_cons	-.847886	2.03628	-0.42	0.677	-4.838922	3.14315
parental	(base alternative)					
relative						
p_immigrant	-.1269439	.160599	-0.79	0.429	-.441712	.1878243
avg_pct_5_yrs_mi	.0023091	.0072967	0.32	0.752	-.0119922	.0166104
avg_pct_foreign~i	-.0016982	.0010061	-1.69	0.091	-.0036701	.0002737
avg_pct_ratio_1~i	.0007362	.0022145	0.33	0.740	-.0036042	.0050766
avg_pct_female_~i	.0019801	.0041225	0.48	0.631	-.0060999	.0100601
medinc	-.0056165	.0090715	-0.62	0.536	-.0233963	.0121633
c_citizen	.7409851	.3958852	1.87	0.061	-.0349356	1.516906
c_white	.1314716	.1976402	0.67	0.506	-.255896	.5188392
c_black	.1538666	.236795	0.65	0.516	-.3102431	.6179763
c_hispanic	.3874518	.2253658	1.72	0.086	-.054257	.8291607
c_asian	.2743369	.3101346	0.88	0.376	-.3335157	.8821895
f_income	.3078458	.064613	4.76	0.000	.1812066	.4344851
p_edu	.1268623	.0755143	1.68	0.093	-.021143	.2748676
f_single	1.10863	.1219071	9.09	0.000	.8696963	1.347563
f_size	.1572927	.0507823	3.10	0.002	.0577611	.2568242
language	-.027732	.1951343	-0.14	0.887	-.4101881	.3547241
c_siblings	-.3811863	.0627674	-6.07	0.000	-.5042082	-.2581644
f_below_poverty	-.1915869	.1482545	-1.29	0.196	-.4821604	.0989866
f_food	.101792	.1026679	0.99	0.321	-.0994334	.3030173
f_wic_pregnant	.166428	.179998	0.92	0.355	-.1863616	.5192175
f_wic_child	-.0925041	.1847845	-0.50	0.617	-.4546749	.2696668
f_food_stamp	.106402	.1819146	0.58	0.559	-.250144	.462948
f_religious	.0023343	.0937404	0.02	0.980	-.1813934	.1860621
m_age_firstbirth	-.0098074	.0106401	-0.92	0.357	-.0306617	.0110468
m_married_birth	.1893033	.1203664	1.57	0.116	-.0466105	.4252172
f_region						
Midwest	.2135201	.7998972	0.27	0.790	-1.35425	1.78129
South	-1.275566	.8162839	-1.56	0.118	-2.875453	.3243212
West	-1.368662	.7921572	-1.73	0.084	-2.921262	.1839374
f_locale						
suburb	.2512604	.1412434	1.78	0.075	-.0255715	.5280924
town	.2283106	.2221438	1.03	0.304	-.2070833	.6637045
rural	.1898424	.1628198	1.17	0.244	-.1292785	.5089634
c_age_prek	.0040941	.010068	0.41	0.684	-.0156388	.0238271
c_female	.0198036	.0889125	0.22	0.824	-.1544616	.1940689
c_lowbirth	.1367182	.1780915	0.77	0.443	-.2123347	.4857711
c_preterm	.0447084	.1250701	0.36	0.721	-.2004245	.2898413
c_breastfed	-.0578992	.1003577	-0.58	0.564	-.2545968	.1387983
c_iep_pk	-.1307954	.2548457	-0.51	0.608	-.6302838	.3686931
c_twin	.2222925	.9421622	0.24	0.813	-1.624311	2.068896
c_birth_cpl	-.0297106	.1330592	-0.22	0.823	-.2905018	.2310806
c_first_word_15	.0004509	.108397	0.00	0.997	-.2120033	.2129052
c_first_step_15	.0316132	.1695824	0.19	0.852	-.3007622	.3639886
state						
4	1.229162	.4077395	3.01	0.003	.4300076	2.028317
5	.9619172	.5192118	1.85	0.064	-.0557193	1.979554
8	1.415551	.5169298	2.74	0.006	.4023871	2.428715
9	.1449213	.7788097	0.19	0.852	-1.381518	1.67136
12	1.213521	.5353209	2.27	0.023	.1643108	2.26273
13	1.056469	.4740556	2.23	0.026	.1273369	1.985601
15	1.743405	.995184	1.75	0.080	-.2071196	3.69393
17	.2541881	.4820332	0.53	0.598	-.6905797	1.198956
18	-.4427364	.5099877	-0.87	0.385	-1.442294	.5568211
19	.1104458	.7495709	0.15	0.883	-1.358686	1.579578
20	-.3487399	.5064552	-0.69	0.491	-1.341374	.643894
22	.5874613	.6591415	0.89	0.373	-.7044324	1.879355
24	.7241166	.4974652	1.46	0.145	-.2508974	1.69913
25	.1687254	.9627806	0.18	0.861	-1.71829	2.055741
27	-.4254832	.4630689	-0.92	0.358	-1.333082	.4821152
28	.5493191	.441366	1.24	0.213	-.3157423	1.41438
29	-.8278661	.5099107	-1.62	0.104	-1.827273	.1715406
30	.5594039	.4387368	1.28	0.202	-.3005044	1.419312

31	-.5753053	.5417185	-1.06	0.288	-1.637054	.4864434
32	1.208029	.4333894	2.79	0.005	.3586011	2.057456
33	-.4871135	.8342265	-0.58	0.559	-2.122167	1.14794
34	-.5402438	.7714989	-0.70	0.484	-2.052354	.9718663
35	.2675144	.524871	0.51	0.610	-.7612139	1.296243
36	.8979999	.7648412	1.17	0.240	-.6010613	2.397061
37	.8942579	.4707355	1.90	0.057	-.0283667	1.816882
39	-.3306362	.4140272	-0.80	0.425	-1.142115	.4808421
40	.2888863	.5384963	0.54	0.592	-.7665472	1.34432
42	-.4768477	.7555947	-0.63	0.528	-1.957786	1.004091
45	1.035091	.4387593	2.36	0.018	.1751388	1.895043
47	.6465589	.4541686	1.42	0.155	-.2435951	1.536713
48	.4273004	.4267402	1.00	0.317	-.4090949	1.263696
49	.6885542	.4197231	1.64	0.101	-.134088	1.511196
50	0	(omitted)				
51	.5188556	.4796748	1.08	0.279	-.4212897	1.459001
53	0	(omitted)				
54	1.494247	.4840116	3.09	0.002	.5456017	2.442892
55	0	(omitted)				
_cons	-2.965587	1.643258	-1.80	0.071	-6.186313	.2551389
state_pre_K						
p_immigrant	-.2274533	.1406726	-1.62	0.106	-.5031665	.0482599
avg_pct_5_yrs_mi	-.0025699	.0061623	-0.42	0.677	-.0146477	.0095079
avg_pct_foreign~i	-.0040239	.0008564	-4.70	0.000	-.0057024	-.0023455
avg_pct_ratio_1~i	.0025623	.0018913	1.35	0.175	-.0011445	.0062691
avg_pct_female_~i	-.0010438	.0036181	-0.29	0.773	-.0081352	.0060477
medinc	.0055838	.007886	0.71	0.479	-.0098725	.0210401
c_citizen	.6878678	.3286893	2.09	0.036	.0436486	1.332087
c_white	-.0303671	.1730941	-0.18	0.861	-.3696253	.3088912
c_black	.2755669	.2067454	1.33	0.183	-.1296465	.6807804
c_hispanic	.2964765	.1979835	1.50	0.134	-.091564	.684517
c_asian	.2433315	.2750019	0.88	0.376	-.2956623	.7823252
f_income	.2029527	.0593001	3.42	0.001	.0867267	.3191787
p_edu	.3108593	.0674907	4.61	0.000	.17858	.4431386
f_single	.3159616	.1141289	2.77	0.006	.0922729	.5396502
f_size	-.0693829	.0531539	-1.31	0.192	-.1735626	.0347967
language	-.0233427	.1671044	-0.14	0.889	-.3508613	.3041759
c_siblings	-.1161032	.0614418	-1.89	0.059	-.2365269	.0043204
f_below_poverty	.0668774	.1306596	0.51	0.609	-.1892107	.3229654
f_food	-.0522214	.0934534	-0.56	0.576	-.2353866	.1309439
f_wic_pregnant	-.1372151	.1522358	-0.90	0.367	-.4355918	.1611616
f_wic_child	.6381663	.1603227	3.98	0.000	.3239397	.952393
f_food_stamp	-.0201058	.1679777	-0.12	0.905	-.349336	.3091244
f_religious	.1769341	.0844368	2.10	0.036	.011441	.3424272
m_age_firstbirth	-.0027742	.0095425	-0.29	0.771	-.0214771	.0159288
m_married_birth	.0615646	.106452	0.58	0.563	-.1470775	.2702068
f_region						
Midwest	-.1987603	.6441248	-0.31	0.758	-1.461222	1.063701
South	-3.022942	.7199577	-4.20	0.000	-4.434033	-1.611851
West	-2.099286	.6392688	-3.28	0.001	-3.352229	-.8463417
f_locale						
suburb	-.0544604	.1222706	-0.45	0.656	-.2941065	.1851856
town	-.0168648	.191545	-0.09	0.930	-.3922862	.3585565
rural	-.111556	.1397434	-0.80	0.425	-.385448	.1623361
c_age_prek	.021663	.0089998	2.41	0.016	.0040237	.0393024
c_female	-.1294653	.0798688	-1.62	0.105	-.2860052	.0270747
c_lowbirth	-.0863523	.1618321	-0.53	0.594	-.4035374	.2308327
c_preterm	.1909833	.1098694	1.74	0.082	-.0243567	.4063234
c_breastfed	.1114069	.0912462	1.22	0.222	-.0674323	.2902461
c_iep_pk	.629482	.2073983	3.04	0.002	.2229887	1.035975
c_twin	.0840959	.860694	0.10	0.922	-1.602833	1.771025
c_birth_cpl	.0876313	.1173367	0.75	0.455	-.1423443	.317607
c_first_word_15	.0345757	.0962031	0.36	0.719	-.1539789	.2231304
c_first_step_15	.0480098	.1492176	0.32	0.748	-.2444513	.3404709
state						

4	.9035926	.3585394	2.52	0.012	.2008683	1.606317
5	2.217648	.5177746	4.28	0.000	1.202828	3.232467
8	.9185509	.4887633	1.88	0.060	-.0394076	1.876509
9	-.7029529	.6361601	-1.10	0.269	-1.949804	.5438979
12	3.655589	.5259966	6.95	0.000	2.624655	4.686523
13	2.52991	.4878847	5.19	0.000	1.573673	3.486146
15	-12.974	827.5173	-0.02	0.987	-1634.878	1608.93
17	.1878948	.4112073	0.46	0.648	-.6180566	.9938463
18	-1.990553	.5154254	-3.86	0.000	-3.000768	-.9803376
19	.9733205	.6321725	1.54	0.124	-.2657148	2.212356
20	-1.294627	.4585874	-2.82	0.005	-2.193442	-.3958118
22	.1833143	.7962213	0.23	0.818	-1.377251	1.743879
24	1.384415	.5230278	2.65	0.008	.3592994	2.409531
25	-1.726235	.8972286	-1.92	0.054	-3.48477	.032301
27	-.8454825	.3964116	-2.13	0.033	-1.622435	-.0685301
28	.3708225	.4934772	0.75	0.452	-.5963751	1.33802
29	-.8513418	.4216241	-2.02	0.043	-1.67771	-.0249738
30	-.5004063	.4168476	-1.20	0.230	-1.317413	.3165999
31	-1.906729	.5383495	-3.54	0.000	-2.961875	-.8515835
32	.056369	.4259717	0.13	0.895	-.7785203	.8912582
33	-3.095014	.857455	-3.61	0.000	-4.775595	-1.414433
34	-1.268699	.6241832	-2.03	0.042	-2.492075	-.0453219
35	-.1658009	.4664918	-0.36	0.722	-1.080108	.7485062
36	-.0824685	.6253786	-0.13	0.895	-1.308188	1.143251
37	1.113776	.5167416	2.16	0.031	.1009808	2.126571
39	-1.576557	.3714853	-4.24	0.000	-2.304655	-.8484595
40	1.754492	.5114636	3.43	0.001	.7520419	2.756942
42	-1.590228	.6115634	-2.60	0.009	-2.78887	-.3915861
45	.8975657	.4967509	1.81	0.071	-.0760481	1.87118
47	1.270868	.4839935	2.63	0.009	.3222583	2.219478
48	1.979412	.4561691	4.34	0.000	1.085337	2.873487
49	.6024777	.3591319	1.68	0.093	-.1014079	1.306363
50	0	(omitted)				
51	1.381102	.5068789	2.72	0.006	.3876372	2.374566
53	0	(omitted)				
54	2.431022	.5111144	4.76	0.000	1.429256	3.432788
55	0	(omitted)				
_cons	-1.635363	1.40487	-1.16	0.244	-4.388857	1.118131

Table B. 3 Stata outputs of estimated coefficients: 25-minute model

Alternative-specific conditional logit		Number of obs =	42,636
Case variable: childid		Number of cases =	7106
Alternative variable: cc_options		Alts per case: min =	6
		avg =	6.0
		max =	6
		Wald chi2(376) =	2873.03
Log likelihood = -10020.854		Prob > chi2 =	0.0000

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
cc_options						
num	.0286358	.0034632	8.27	0.000	.0218481	.0354234
center						
p_immigrant	-.4932627	.1390006	-3.55	0.000	-.7656988	-.2208265
avg_pct_5_yrs_mi	-.0085899	.0071339	-1.20	0.229	-.0225721	.0053922
avg_pct_foreign~i	-.00364	.0009188	-3.96	0.000	-.0054408	-.0018393
avg_pct_ratio_1~i	.0037699	.0020977	1.80	0.072	-.0003416	.0078813
avg_pct_female_~i	-.0002703	.0038783	-0.07	0.944	-.0078717	.007331
medinc	.0368185	.0083769	4.40	0.000	.0204002	.0532369
c_citizen	.5828011	.306125	1.90	0.057	-.0171929	1.182795
c_white	.1059923	.1684645	0.63	0.529	-.2241921	.4361766
c_black	-.1078547	.2095865	-0.51	0.607	-.5186367	.3029273
c_hispanic	-.038617	.199013	-0.19	0.846	-.4286753	.3514413
c_asian	.3635676	.2595919	1.40	0.161	-.1452232	.8723584
f_income	.4493405	.0557147	8.07	0.000	.3401416	.5585394
p_edu	.4566009	.0622295	7.34	0.000	.3346333	.5785686
f_single	.3556937	.1202503	2.96	0.003	.1200075	.59138
f_size	-.2224467	.0641088	-3.47	0.001	-.3480976	-.0967958
language	-.4205949	.1855437	-2.27	0.023	-.7842538	-.056936
c_siblings	-.0797216	.0722404	-1.10	0.270	-.2213101	.0618669
f_below_poverty	-.0842419	.1458102	-0.58	0.563	-.3700247	.2015408
f_food	-.00203	.1034038	-0.02	0.984	-.2046977	.2006377
f_wic_pregnant	-.1543042	.1623184	-0.95	0.342	-.4724425	.1638341
f_wic_child	.0112186	.163678	0.07	0.945	-.3095844	.3320216
f_food_stamp	-.041199	.1810834	-0.23	0.820	-.3961159	.3137179
f_religious	.2099828	.0818862	2.56	0.010	.0494888	.3704767
m_age_firstbirth	.0246995	.0089869	2.75	0.006	.0070855	.0423135
m_married_birth	.1350824	.1131728	1.19	0.233	-.0867322	.356897
f_region						
Midwest	-.3118461	.6532521	-0.48	0.633	-1.592197	.9685046
South	-1.214487	.642057	-1.89	0.059	-2.472896	.0439214
West	-1.79611	.6234986	-2.88	0.004	-3.018145	-.574075
f_locale						
suburb	.1745477	.1208209	1.44	0.149	-.0622569	.4113523
town	.0714502	.1897608	0.38	0.707	-.3004741	.4433746
rural	-.0955693	.1372727	-0.70	0.486	-.3646188	.1734803
c_age_prek	-.001395	.008727	-0.16	0.873	-.0184996	.0157096
c_female	-.045698	.0768538	-0.59	0.552	-.1963287	.1049326
c_lowbirth	-.0207666	.1599401	-0.13	0.897	-.3342435	.2927102
c_preterm	.1428423	.1079255	1.32	0.186	-.0686877	.3543724
c_breastfed	.2412647	.090726	2.66	0.008	.0634449	.4190844
c_iep_pk	-.7043577	.259089	-2.72	0.007	-1.212163	-.1965527
c_twin	.2643952	.7468959	0.35	0.723	-1.199494	1.728284
c_birth_cpl	-.075387	.116123	-0.65	0.516	-.3029839	.1522099
c_first_word_15	-.1510783	.0956174	-1.58	0.114	-.3384849	.0363283
c_first_step_15	-.2954605	.1580606	-1.87	0.062	-.6052537	.0143326
state						
4	.1573733	.3518932	0.45	0.655	-.5323246	.8470712
5	-1.232483	.6292371	-1.96	0.050	-2.465765	.0007994
8	-.2983479	.444651	-0.67	0.502	-1.169848	.5731521

9	-1.00403	.6251673	-1.61	0.108	-2.229335	.2212758
12	.266038	.4216744	0.63	0.528	-.5604288	1.092505
13	-.9242672	.4021965	-2.30	0.022	-1.712558	-.1359766
15	1.87998	.7992054	2.35	0.019	.3135663	3.446394
17	-.2397331	.4409986	-0.54	0.587	-1.104074	.6246083
18	-.4479108	.4401349	-1.02	0.309	-1.310559	.4147378
19	-.3643886	.7266545	-0.50	0.616	-1.788605	1.059828
20	-1.131434	.4880523	-2.32	0.020	-2.087998	-.1748687
22	-.665131	.6604028	-1.01	0.314	-1.959497	.6292348
24	-1.186443	.401513	-2.95	0.003	-1.973394	-.3994922
25	-1.886777	.8450332	-2.23	0.026	-3.543012	-.2305425
27	-.4160941	.4065413	-1.02	0.306	-1.2129	.3807123
28	-.03713	.3441728	-0.11	0.914	-.7116962	.6374362
29	-.9658633	.4255084	-2.27	0.023	-1.799844	-.1318821
30	.4432588	.34568	1.28	0.200	-.2342615	1.120779
31	-.5601401	.453262	-1.24	0.217	-1.448517	.328237
32	.9095023	.3586459	2.54	0.011	.2065693	1.612435
33	-1.117168	.6522459	-1.71	0.087	-2.395547	.1612105
34	-2.792514	.6227421	-4.48	0.000	-4.013066	-1.571962
35	-.4472573	.4702518	-0.95	0.342	-1.368934	.4744193
36	-.7899704	.627015	-1.26	0.208	-2.018897	.4389564
37	.1397829	.3730117	0.37	0.708	-.5913067	.8708724
39	-1.106138	.3729192	-2.97	0.003	-1.837046	-.3752293
40	-.8892544	.4645323	-1.91	0.056	-1.799721	.0212122
42	-1.599849	.6074336	-2.63	0.008	-2.790397	-.4093016
45	.2706798	.3555117	0.76	0.446	-.4261103	.9674699
47	.4413248	.3512969	1.26	0.209	-.2472044	1.129854
48	.4276887	.3291166	1.30	0.194	-.2173679	1.072745
49	-.0617319	.3196166	-0.19	0.847	-.6881688	.564705
50	0	(omitted)				
51	-.0546976	.3683496	-0.15	0.882	-.7766496	.6672544
53	0	(omitted)				
54	.2764415	.3920528	0.71	0.481	-.4919679	1.044851
55	0	(omitted)				
_cons	-2.889333	1.384331	-2.09	0.037	-5.602572	-.1760949
head_start						
p_immigrant	-.0051513	.1928965	-0.03	0.979	-.3832214	.3729189
avg_pct_5_yrs_mi	-.0210638	.0100152	-2.10	0.035	-.0406932	-.0014343
avg_pct_foreign~i	.0007722	.0010955	0.70	0.481	-.0013748	.0029193
avg_pct_ratio_1~i	.0008195	.0027164	0.30	0.763	-.0045045	.0061435
avg_pct_female_~i	-.010778	.0050594	-2.13	0.033	-.0206942	-.0008618
medinc	.0024568	.0117509	0.21	0.834	-.0205745	.0254881
c_citizen	.2497835	.434487	0.57	0.565	-.6017954	1.101362
c_white	.1738075	.2405843	0.72	0.470	-.297729	.6453441
c_black	.870975	.2657357	3.28	0.001	.3501426	1.391807
c_hispanic	.6137918	.2696182	2.28	0.023	.0853499	1.142234
c_asian	-.0691659	.4297587	-0.16	0.872	-.9114776	.7731457
f_income	.0991906	.0813789	1.22	0.223	-.0603091	.2586903
p_edu	.2772136	.092776	2.99	0.003	.0953759	.4590513
f_single	.6217548	.136191	4.57	0.000	.3548253	.8886843
f_size	-.0259583	.0608028	-0.43	0.669	-.1451295	.093213
language	-.1577145	.2270845	-0.69	0.487	-.602792	.2873629
c_siblings	-.1904232	.0732141	-2.60	0.009	-.3339202	-.0469262
f_below_poverty	.3457201	.1620462	2.13	0.033	.0281153	.6633249
f_food	.0095397	.1123534	0.08	0.932	-.2106689	.2297484
f_wic_pregnant	.1377439	.1965413	0.70	0.483	-.2474699	.5229578
f_wic_child	.637252	.2124156	3.00	0.003	.2209251	1.053579
f_food_stamp	-.0788507	.2025633	-0.39	0.697	-.4758675	.318166
f_religious	.2608563	.1101653	2.37	0.018	.0449363	.4767763
m_age_firstbirth	-.008728	.0127167	-0.69	0.492	-.0336523	.0161963
m_married_birth	-.1843463	.1337692	-1.38	0.168	-.4465291	.0778366
f_region						
Midwest	-.8832919	.8773381	-1.01	0.314	-2.602843	.8362593
South	-1.285923	.8191083	-1.57	0.116	-2.891346	.3194996
West	-1.216738	.7959865	-1.53	0.126	-2.776843	.3433672
f_locale						
suburb	.0979006	.1698766	0.58	0.564	-.2350514	.4308527

town	.259254	.2499128	1.04	0.300	-.2305662	.7490741
rural	.2121071	.1916593	1.11	0.268	-.1635382	.5877523
c_age_prek	.0086629	.0119798	0.72	0.470	-.0148171	.032143
c_female	-.0809821	.1042136	-0.78	0.437	-.285237	.1232728
c_lowbirth	.199045	.1978754	1.01	0.314	-.1887836	.5868736
c_preterm	.0830567	.14362	0.58	0.563	-.1984334	.3645468
c_breastfed	.0691039	.1166154	0.59	0.553	-.159458	.2976658
c_iep_pk	.443662	.2566341	1.73	0.084	-.0593317	.9466556
c_twin	.4535973	.9722687	0.47	0.641	-1.452014	2.359209
c_birth_cpl	.0377578	.152922	0.25	0.805	-.2619637	.3374794
c_first_word_15	-.0278923	.1305875	-0.21	0.831	-.2838392	.2280546
c_first_step_15	-.260315	.2082072	-1.25	0.211	-.6683936	.1477636
state						
4	-.2583257	.4704531	-0.55	0.583	-1.180397	.6637454
5	.3568733	.5412326	0.66	0.510	-.7039231	1.41767
8	.9343751	.5912043	1.58	0.114	-.2243641	2.093114
9	-.3318657	.8148186	-0.41	0.684	-1.928881	1.265149
12	.473286	.5497318	0.86	0.389	-.6041686	1.550741
13	.5842726	.4731191	1.23	0.217	-.3430238	1.511569
15	.7767657	1.287518	0.60	0.546	-1.746724	3.300255
17	1.044475	.6026337	1.73	0.083	-.1366657	2.225615
18	-.0199118	.7267583	-0.03	0.978	-1.444332	1.404508
19	1.02183	.9442372	1.08	0.279	-.8288408	2.872501
20	.8286958	.6148488	1.35	0.178	-.3763857	2.033777
22	.0272492	.6802781	0.04	0.968	-1.306071	1.36057
24	.1232438	.6011928	0.20	0.838	-1.055072	1.30156
25	-.2715126	1.020531	-0.27	0.790	-2.271717	1.728692
27	1.337095	.5969637	2.24	0.025	.1670679	2.507123
28	.7975678	.4090024	1.95	0.051	-.0040622	1.599198
29	.1486381	.6750072	0.22	0.826	-1.174352	1.471628
30	.1005867	.4718377	0.21	0.831	-.8241982	1.025372
31	1.242926	.6580305	1.89	0.059	-.04679	2.532642
32	-.9804781	.6282216	-1.56	0.119	-2.21177	.2508136
33	-.2530353	.8584366	-0.29	0.768	-1.93554	1.42947
34	-1.81936	.8525672	-2.13	0.033	-3.490361	-.1483588
35	.058586	.7089813	0.08	0.934	-1.330992	1.448164
36	.3040481	.7850006	0.39	0.699	-1.234525	1.842621
37	.7701974	.4584445	1.68	0.093	-.1283373	1.668732
39	-.25355	.5933229	-0.43	0.669	-1.416441	.9093415
40	-.016734	.5617473	-0.03	0.976	-1.117738	1.08427
42	-.3856944	.7584694	-0.51	0.611	-1.872267	1.100878
45	-.2730176	.5030876	-0.54	0.587	-1.259051	.713016
47	.0416699	.4708321	0.09	0.929	-.881144	.9644837
48	-.4182979	.4420672	-0.95	0.344	-1.284734	.448138
49	.0214541	.47077	0.05	0.964	-.9012381	.9441463
50	0	(omitted)				
51	.3052162	.4827169	0.63	0.527	-.6408915	1.251324
53	0	(omitted)				
54	1.334579	.4905092	2.72	0.007	.3731987	2.295959
55	0	(omitted)				
_cons	1.060296	1.860212	0.57	0.569	-2.585653	4.706245
non_relative						
p_immigrant	-.3588962	.2217994	-1.62	0.106	-.7936151	.0758226
avg_pct_5_yrs_mi	-.0076039	.0115173	-0.66	0.509	-.0301775	.0149697
avg_pct_foreign~i	-.0030815	.0015483	-1.99	0.047	-.0061161	-.0000469
avg_pct_ratio_1~i	-.0015562	.0033879	-0.46	0.646	-.0081964	.005084
avg_pct_female_~i	.0033479	.0055922	0.60	0.549	-.0076127	.0143085
medinc	.0057917	.0128371	0.45	0.652	-.0193685	.0309519
c_citizen	.3651994	.5693907	0.64	0.521	-.7507858	1.481185
c_white	.945221	.3179196	2.97	0.003	.32211	1.568332
c_black	.7277391	.3976423	1.83	0.067	-.0516255	1.507104
c_hispanic	1.160343	.3556076	3.26	0.001	.4633654	1.857321
c_asian	-.4952206	.6332839	-0.78	0.434	-1.736434	.7459932
f_income	.4787488	.0815113	5.87	0.000	.3189896	.6385081
p_edu	.4694567	.0886158	5.30	0.000	.295773	.6431403
f_single	.4636023	.1809386	2.56	0.010	.1089691	.8182355
f_size	-.1677647	.1060061	-1.58	0.114	-.3755328	.0400034

language	-.2638631	.3419114	-0.77	0.440	-.9339971	.406271
c_siblings	-.2204189	.1174986	-1.88	0.061	-.4507119	.0098741
f_below_poverty	-.1689758	.2383169	-0.71	0.478	-.6360683	.2981167
f_food	.1774784	.1546927	1.15	0.251	-.1257137	.4806704
f_wic_pregnant	.0645954	.2374836	0.27	0.786	-.400864	.5300548
f_wic_child	-.1660825	.2373118	-0.70	0.484	-.631205	.29904
f_food_stamp	.2499143	.2543992	0.98	0.326	-.248699	.7485277
f_religious	.0222926	.1198648	0.19	0.852	-.212638	.2572233
m_age_firstbirth	.0034619	.0132245	0.26	0.793	-.0224577	.0293814
m_married_birth	.0425369	.1721663	0.25	0.805	-.2949028	.3799766
f_region						
Midwest	-.6909573	.797197	-0.87	0.386	-2.253435	.8715201
South	-2.76411	1.007111	-2.74	0.006	-4.738012	-.7902078
West	-1.617611	.7560376	-2.14	0.032	-3.099417	-.1358043
f_locale						
suburb	-.0795284	.1899322	-0.42	0.675	-.4517888	.2927319
town	-.0624252	.2565801	-0.24	0.808	-.5653129	.4404625
rural	-.0499662	.2100303	-0.24	0.812	-.4616179	.3616856
c_age_prek	-.0111004	.0129662	-0.86	0.392	-.0365136	.0143128
c_female	.0224958	.1114312	0.20	0.840	-.1959054	.2408971
c_lowbirth	-.1937205	.23745	-0.82	0.415	-.6591139	.2716728
c_preterm	.4186348	.1514777	2.76	0.006	.1217439	.7155256
c_breastfed	.2527513	.1361246	1.86	0.063	-.014048	.5195506
c_iep_pk	-.3952698	.3342806	-1.18	0.237	-1.050448	.2599081
c_twin	-.073962	1.265439	-0.06	0.953	-2.554178	2.406254
c_birth_cpl	.1063527	.160425	0.66	0.507	-.2080745	.4207799
c_first_word_15	.003177	.1366405	0.02	0.981	-.2646334	.2709875
c_first_step_15	-.1222419	.2274814	-0.54	0.591	-.5680972	.3236133
state						
4	.3256156	.5072606	0.64	0.521	-.6685969	1.319828
5	-.2232547	1.276916	-0.17	0.861	-2.725964	2.279455
8	-.198857	.6565626	-0.30	0.762	-1.485696	1.087982
9	-1.929917	.7975203	-2.42	0.016	-3.493028	-.3668055
12	.2218349	1.025584	0.22	0.829	-1.788273	2.231943
13	.3084127	.9719492	0.32	0.751	-1.596573	2.213398
15	.5712678	1.296074	0.44	0.659	-1.968991	3.111526
17	1.097525	.5483259	2.00	0.045	.0228256	2.172224
18	-.3208663	.6116141	-0.52	0.600	-1.519608	.8778754
19	1.668254	.7488323	2.23	0.026	.2005692	3.135938
20	.018352	.6443766	0.03	0.977	-1.244603	1.281307
22	1.108071	1.09943	1.01	0.314	-1.046772	3.262914
24	1.112817	.8544582	1.30	0.193	-.5618907	2.787524
25	-2.751157	1.319135	-2.09	0.037	-5.336615	-.1656991
27	1.254656	.5315294	2.36	0.018	.2128778	2.296435
28	.2779573	.8837461	0.31	0.753	-1.454153	2.010068
29	-1.100768	.6300926	-1.75	0.081	-2.335727	.1341911
30	.051585	.490578	0.11	0.916	-.9099301	1.0131
31	-.9522277	.6769576	-1.41	0.160	-2.27904	.3745848
32	-.0435544	.5783841	-0.08	0.940	-1.177166	1.090058
33	-2.622656	.9417974	-2.78	0.005	-4.468545	-.7767668
34	-2.549502	.7876728	-3.24	0.001	-4.093312	-1.005692
35	-.4349949	.7212195	-0.60	0.546	-1.848559	.9785694
36	-.3292717	.7384906	-0.45	0.656	-1.776687	1.118143
37	-.3690265	1.051331	-0.35	0.726	-2.429596	1.691544
39	-.4645238	.5093708	-0.91	0.362	-1.462872	.5338247
40	.1651669	1.05969	0.16	0.876	-1.911787	2.242121
42	-1.80342	.7370106	-2.45	0.014	-3.247934	-.3589059
45	.9320675	.8355848	1.12	0.265	-.7056485	2.569784
47	.2948898	.890954	0.33	0.741	-1.451348	2.041127
48	1.023491	.8014168	1.28	0.202	-.5472576	2.594239
49	1.760455	.3942385	4.47	0.000	.9877616	2.533148
50	0	(omitted)				
51	1.007533	.8424492	1.20	0.232	-.6436373	2.658703
53	0	(omitted)				
54	1.341716	.8490189	1.58	0.114	-.3223301	3.005763
55	0	(omitted)				

_cons	-2.326896	1.98755	-1.17	0.242	-6.222422	1.568629
parental	(base alternative)					
relative						
p_immigrant	-.1288108	.1606715	-0.80	0.423	-.4437211	.1860995
avg_pct_5_yrs_mi	-.0057128	.0081198	-0.70	0.482	-.0216272	.0102017
avg_pct_foreign~i	-.0013358	.0009854	-1.36	0.175	-.0032672	.0005956
avg_pct_ratio_1~i	.0023325	.0023263	1.00	0.316	-.002227	.006892
avg_pct_female_~i	-.0009644	.0043606	-0.22	0.825	-.0095111	.0075823
medinc	.0059602	.0096152	0.62	0.535	-.0128852	.0248056
c_citizen	.7275442	.3958653	1.84	0.066	-.0483374	1.503426
c_white	.123072	.1975543	0.62	0.533	-.2641272	.5102713
c_black	.1546766	.2368031	0.65	0.514	-.309449	.6188022
c_hispanic	.3730223	.225218	1.66	0.098	-.0683968	.8144414
c_asian	.2630851	.3106008	0.85	0.397	-.3456813	.8718514
f_income	.3017929	.0645442	4.68	0.000	.1752887	.4282971
p_edu	.1203796	.0755883	1.59	0.111	-.0277707	.2685299
f_single	1.10304	.1217917	9.06	0.000	.8643332	1.341748
f_size	.15657	.0507354	3.09	0.002	.0571305	.2560096
language	-.0417159	.1953322	-0.21	0.831	-.42456	.3411282
c_siblings	-.3808436	.0627698	-6.07	0.000	-.5038701	-.2578172
f_below_poverty	-.1992772	.1481854	-1.34	0.179	-.4897152	.0911609
f_food	.1007828	.1026976	0.98	0.326	-.1005007	.3020663
f_wic_pregnant	.1566617	.1801956	0.87	0.385	-.1965152	.5098386
f_wic_child	-.0808027	.1849934	-0.44	0.662	-.4433832	.2817778
f_food_stamp	.1063682	.181975	0.58	0.559	-.2502963	.4630326
f_religious	.0035713	.0937299	0.04	0.970	-.180136	.1872785
m_age_firstbirth	-.0101605	.0106371	-0.96	0.339	-.0310088	.0106878
m_married_birth	.1880095	.1202376	1.56	0.118	-.0476519	.4236709
f_region						
Midwest	.3302691	.8054707	0.41	0.682	-1.248424	1.908963
South	-1.157858	.8178864	-1.42	0.157	-2.760886	.4451695
West	-1.381583	.7935685	-1.74	0.082	-2.936949	.1737826
f_locale						
suburb	.2414907	.1409798	1.71	0.087	-.0348247	.5178061
town	.2471217	.2201891	1.12	0.262	-.184441	.6786844
rural	.1926974	.1600997	1.20	0.229	-.1210923	.506487
c_age_prek	.0037802	.0100592	0.38	0.707	-.0159354	.0234959
c_female	.0186245	.0889038	0.21	0.834	-.1556238	.1928729
c_lowbirth	.1447417	.178049	0.81	0.416	-.2042279	.4937113
c_preterm	.0423456	.1251344	0.34	0.735	-.2029133	.2876044
c_breastfed	-.0582679	.1003339	-0.58	0.561	-.2549187	.1383828
c_iep_pk	-.1438339	.2549318	-0.56	0.573	-.643491	.3558233
c_twin	.2374502	.9401391	0.25	0.801	-1.605189	2.080089
c_birth_cpl	-.0280793	.1330524	-0.21	0.833	-.2888572	.2326987
c_first_word_15	.0058108	.1084478	0.05	0.957	-.2067429	.2183646
c_first_step_15	.0336395	.1696728	0.20	0.843	-.2989131	.3661922
state						
4	1.303896	.40993	3.18	0.001	.5004478	2.107344
5	.9903422	.5132526	1.93	0.054	-.0156144	1.996299
8	1.492073	.5149591	2.90	0.004	.4827715	2.501374
9	.1240612	.7777947	0.16	0.873	-1.400388	1.648511
12	1.020854	.5331259	1.91	0.056	-.0240536	2.065762
13	.9734438	.4742479	2.05	0.040	.0439349	1.902953
15	1.627701	.9892875	1.65	0.100	-.3112672	3.566669
17	.2349579	.4919008	0.48	0.633	-.72915	1.199066
18	-.4152947	.5187225	-0.80	0.423	-1.431972	.6013827
19	.2818035	.7537034	0.37	0.708	-1.195428	1.759035
20	-.3130855	.5150753	-0.61	0.543	-1.322615	.6964436
22	.5062527	.6544359	0.77	0.439	-.7764181	1.788923
24	.5675294	.5135548	1.11	0.269	-.4390194	1.574078
25	.1632142	.9633627	0.17	0.865	-1.724942	2.05137
27	-.2871337	.4736127	-0.61	0.544	-1.215397	.6411301
28	.5860413	.4409922	1.33	0.184	-.2782876	1.45037
29	-.8438319	.5203939	-1.62	0.105	-1.863785	.1761215
30	.7228758	.4403176	1.64	0.101	-.1401309	1.585883

31	-.4695527	.5492548	-0.85	0.393	-1.546072	.606967
32	1.260021	.4314752	2.92	0.003	.4143447	2.105696
33	-.4841485	.8333137	-0.58	0.561	-2.117413	1.149116
34	-.7115794	.7721712	-0.92	0.357	-2.225007	.8018484
35	.4351721	.5622319	0.77	0.439	-.6667822	1.537126
36	.8344734	.7648185	1.09	0.275	-.6645433	2.33349
37	.9110839	.4712852	1.93	0.053	-.0126181	1.834786
39	-.3582644	.428128	-0.84	0.403	-1.19738	.480851
40	.2516391	.5380002	0.47	0.640	-.8028219	1.3061
42	-.477996	.7546982	-0.63	0.526	-1.957177	1.001185
45	1.079268	.4435862	2.43	0.015	.2098546	1.948681
47	.6458987	.455502	1.42	0.156	-.2468688	1.538666
48	.3886542	.4322456	0.90	0.369	-.4585315	1.23584
49	.7079478	.4203021	1.68	0.092	-.1158291	1.531725
50	0	(omitted)				
51	.3923739	.4779925	0.82	0.412	-.5444742	1.329222
53	0	(omitted)				
54	1.403051	.4842274	2.90	0.004	.4539828	2.352119
55	0	(omitted)				
_cons	-2.695807	1.63269	-1.65	0.099	-5.89582	.5042056
state_pre_K						
p_immigrant	-.2427813	.1407934	-1.72	0.085	-.5187312	.0331687
avg_pct_5_yrs_mi	-.0117847	.00705	-1.67	0.095	-.0256023	.002033
avg_pct_foreign~i	-.0040655	.0008494	-4.79	0.000	-.0057303	-.0024008
avg_pct_ratio_1~i	.0042141	.0019844	2.12	0.034	.0003248	.0081035
avg_pct_female_~i	-.0020944	.0039223	-0.53	0.593	-.009782	.0055932
medinc	.0183285	.0084947	2.16	0.031	.0016791	.0349779
c_citizen	.6393418	.3283682	1.95	0.052	-.0042481	1.282932
c_white	-.0295827	.1730723	-0.17	0.864	-.3687981	.3096328
c_black	.2589466	.2067302	1.25	0.210	-.1462371	.6641303
c_hispanic	.2691553	.1979538	1.36	0.174	-.118827	.6571376
c_asian	.2420717	.2752878	0.88	0.379	-.2974826	.7816259
f_income	.198511	.0592561	3.35	0.001	.0823712	.3146508
p_edu	.3062073	.0675043	4.54	0.000	.1739012	.4385133
f_single	.3104653	.1140479	2.72	0.006	.0869356	.533995
f_size	-.0752838	.0531452	-1.42	0.157	-.1794466	.0288789
language	-.0481983	.1672621	-0.29	0.773	-.376026	.2796293
c_siblings	-.1110402	.0614728	-1.81	0.071	-.2315246	.0094442
f_below_poverty	.0629194	.1305451	0.48	0.630	-.1929444	.3187831
f_food	-.059383	.0934925	-0.64	0.525	-.242625	.123859
f_wic_pregnant	-.1368169	.152671	-0.90	0.370	-.4360466	.1624128
f_wic_child	.6511057	.1606576	4.05	0.000	.3362226	.9659888
f_food_stamp	-.0230417	.1679903	-0.14	0.891	-.3522967	.3062132
f_religious	.1791138	.0844467	2.12	0.034	.0136014	.3446263
m_age_firstbirth	-.0034131	.0095424	-0.36	0.721	-.022116	.0152898
m_married_birth	.062541	.106431	0.59	0.557	-.14606	.2711421
f_region						
Midwest	-.0099377	.6499891	-0.02	0.988	-1.283893	1.264018
South	-2.769004	.7209554	-3.84	0.000	-4.182051	-1.355957
West	-2.014346	.6409611	-3.14	0.002	-3.270607	-.7580856
f_locale						
suburb	-.0450702	.1222265	-0.37	0.712	-.2846298	.1944894
town	.133562	.1915007	0.70	0.486	-.2417725	.5088964
rural	.0067137	.1386389	0.05	0.961	-.2650135	.2784409
c_age_prek	.0209521	.0090016	2.33	0.020	.0033093	.038595
c_female	-.1320835	.0798772	-1.65	0.098	-.28864	.024473
c_lowbirth	-.076514	.1618274	-0.47	0.636	-.3936899	.2406618
c_preterm	.1949443	.1099015	1.77	0.076	-.0204587	.4103472
c_breastfed	.1114184	.0912483	1.22	0.222	-.0674249	.2902617
c_iep_pk	.6147246	.2074773	2.96	0.003	.2080767	1.021373
c_twin	.1162633	.8544314	0.14	0.892	-1.558392	1.790918
c_birth_cpl	.0963679	.1172929	0.82	0.411	-.1335221	.3262578
c_first_word_15	.0425746	.0962593	0.44	0.658	-.1460901	.2312394
c_first_step_15	.0518056	.149419	0.35	0.729	-.2410502	.3446614
state						

4	.9447582	.360058	2.62	0.009	.2390575	1.650459
5	2.204502	.5132765	4.29	0.000	1.198499	3.210506
8	.8281366	.4881329	1.70	0.090	-.1285863	1.784859
9	-.6959317	.6357452	-1.09	0.274	-1.941969	.550106
12	3.483739	.5251059	6.63	0.000	2.45455	4.512927
13	2.398881	.4877132	4.92	0.000	1.44298	3.354781
15	-13.96043	1249.689	-0.01	0.991	-2463.306	2435.385
17	.0886567	.4204952	0.21	0.833	-.7354987	.9128121
18	-1.942621	.5237022	-3.71	0.000	-2.969059	-.9161837
19	1.08947	.6366073	1.71	0.087	-.1582574	2.337197
20	-1.259453	.4677635	-2.69	0.007	-2.176252	-.3426531
22	.1277221	.7932424	0.16	0.872	-1.427004	1.682449
24	1.020718	.535957	1.90	0.057	-.0297381	2.071175
25	-1.589398	.8989915	-1.77	0.077	-3.351389	.1725928
27	-.7651776	.4080843	-1.88	0.061	-1.565008	.034653
28	.415216	.4929918	0.84	0.400	-.5510301	1.381462
29	-.9388344	.4331448	-2.17	0.030	-1.787783	-.0898863
30	-.3902566	.4193105	-0.93	0.352	-1.21209	.4315769
31	-1.870031	.5461564	-3.42	0.001	-2.940478	-.7995838
32	.0914663	.4245371	0.22	0.829	-.7406111	.9235437
33	-2.990307	.8570703	-3.49	0.000	-4.670134	-1.310481
34	-1.382905	.6256122	-2.21	0.027	-2.609083	-.1567277
35	.1296538	.5009509	0.26	0.796	-.8521919	1.111499
36	-.0062928	.6258072	-0.01	0.992	-1.232852	1.220267
37	1.089089	.5169036	2.11	0.035	.0759769	2.102202
39	-1.631522	.3843603	-4.24	0.000	-2.384855	-.87819
40	1.650716	.5107312	3.23	0.001	.6497009	2.65173
42	-1.493035	.6107618	-2.44	0.015	-2.690106	-.2959636
45	.9182858	.5001359	1.84	0.066	-.0619625	1.898534
47	1.187375	.4846734	2.45	0.014	.2374331	2.137318
48	1.879553	.4594705	4.09	0.000	.9790073	2.780099
49	.5780219	.359391	1.61	0.108	-.1263714	1.282415
50	0	(omitted)				
51	1.11316	.5052757	2.20	0.028	.1228379	2.103482
53	0	(omitted)				
54	2.268735	.510911	4.44	0.000	1.267368	3.270102
55	0	(omitted)				
_cons	-1.881443	1.429173	-1.32	0.188	-4.68257	.9196845

APPENDIX C MARGINAL EFFECT OUTPUTS BY BUFFER SIZE

Table C. 1 Stata outputs of marginal effects: 5-mile model

Equation Name	Alternative
center	center
head_start	head start
non_relative	non-relative
parental	parental
relative	relative
state_pre_K	state pre-K

Pr(choice = center|1 selected) = .43956295

variable	dp/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
num							
center	.012237	.001444	8.47	0.000	.009405	.015068	3.125
head_start	-.001151	.000614	-1.88	0.061	-.002353	.000052	.48437
non_relative	-.002269	.000979	-2.32	0.021	-.004189	-.00035	.21544
parental	-.001626	.000803	-2.03	0.043	-.0032	-.000053	.19631
relative	-.001413	.000719	-1.96	0.049	-.002823	-3.4e-06	.12778
state_pre_K	-.005777	.001326	-4.36	0.000	-.008376	-.003179	1.298
casevars							
p_immigrant	-.071434	.028836	-2.48	0.013	-.127951	-.014918	.198
avg_pct_5_~i	.000571	.001012	0.56	0.573	-.001412	.002554	64.724
avg_pct_fo~i	-.000108	.000168	-0.64	0.520	-.000437	.000221	98.667
avg_pct_ra~i	-.00029	.000324	-0.89	0.371	-.000925	.000345	136.87
avg_pct_fe~i	-.00032	.000585	-0.55	0.584	-.001466	.000826	221.9
medinc	.003401	.001169	2.91	0.004	.00111	.005693	58.61
c_citizen	.035098	.073222	0.48	0.632	-.108413	.17861	.98607
c_white	-.024343	.038967	-0.62	0.532	-.100717	.052031	.61483
c_black	-.100834	.045499	-2.22	0.027	-.19001	-.011659	.11272
c_hispanic	-.117854	.045186	-2.61	0.009	-.206416	-.029291	.17183
c_asian	.075853	.058243	1.30	0.193	-.038302	.190008	.041655
f_income	.052851	.013129	4.03	0.000	.027118	.078584	2.6849
p_edu	.044222	.013174	3.36	0.001	.018402	.070041	2.4118
f_single	-.016934	.027844	-0.61	0.543	-.071507	.037639	.23923
f_size	-.043327	.015082	-2.87	0.004	-.072887	-.013767	4.5348
language	-.077717	.041612	-1.87	0.062	-.159274	.003841	.11061
c_siblings	.019048	.016751	1.14	0.255	-.013783	.051879	1.4813
f_below_po~y	-.025802	.032962	-0.78	0.434	-.090407	.038803	.21545
f_food	-.003024	.023312	-0.13	0.897	-.048715	.042667	1.1354
f_wic_preg~t	-.039517	.033857	-1.17	0.243	-.105876	.026843	.39291
f_wic_child	-.076499	.037634	-2.03	0.042	-.15026	-.002739	.43428
f_food_stamp	-.021875	.037992	-0.58	0.565	-.096337	.052587	.05615
f_religious	.021256	.016671	1.28	0.202	-.011419	.053931	.57895
m_age_firs~h	.006654	.001749	3.81	0.000	.003227	.010082	24.691
m_married_~h	.023003	.02394	0.96	0.337	-.023918	.069923	.71967
1.f_region	-.094445	.090425	-1.04	0.296	-.271675	.082784	0
2.f_locale	.039615	.025293	1.57	0.117	-.009958	.089188	1
c_age_prek	-.002647	.0018	-1.47	0.141	-.006176	.000881	54.471
c_female	.00484	.015323	0.32	0.752	-.025193	.034872	.48508
c_lowbirth	.007081	.031754	0.22	0.824	-.055156	.069319	.082043
c_preterm	-.011868	.021479	-0.55	0.581	-.053965	.030229	.20419
c_breastfed	.033336	.018546	1.80	0.072	-.003014	.069685	.71264
c_iep_pk	-.233586	.056793	-4.11	0.000	-.344899	-.122274	.033634
c_twin	.029979	.136756	0.22	0.826	-.238058	.298016	.002674
c_birth_cpl	-.034388	.02244	-1.53	0.125	-.07837	.009595	.13932
c_first_w~15	-.038369	.018998	-2.02	0.043	-.075605	-.001133	.22699
c_first_s~15	-.06882	.032126	-2.14	0.032	-.131785	-.005854	.072615
4.state	-.079182	.077039	-1.03	0.304	-.230177	.071812	1

dp/dx for factor levels is the discrete change from the base level

Pr(choice = head start|1 selected) = .0526957

```
------------------------------------------------------------------------------
variable     |   dp/dx   Std. Err.    z     P>|z|  [    95% C.I.    ]       X
-------------+----------------------------------------------------------------
num          |
      center | -.001151   .000614   -1.88   0.061  -.002353   .000052     3.125
  head_start |   .00248   .001291    1.92   0.055   -.00005   .005009    .48437
non_relative | -.000272   .000184   -1.48   0.138  -.000632   .000088    .21544
    parental | -.000195   .000144   -1.35   0.176  -.000477   .000087    .19631
    relative | -.000169   .000127   -1.34   0.181  -.000418   .000079    .12778
 state_pre_K | -.000693   .000413   -1.68   0.093  -.001501   .000116     1.298
-------------+----------------------------------------------------------------
casevars     |
 p_immigrant |  .017268   .012405    1.39   0.164  -.007046   .041583      .198
avg_pct_5_~i | -.000726   .000468   -1.55   0.121  -.001644   .000192    64.724
avg_pct_fo~i |  .000134    .00008    1.69   0.092  -.000022    .00029    98.667
avg_pct_ra~i | -7.4e-06   .000093   -0.08   0.937  -.000189   .000175    136.87
avg_pct_fe~i | -.000327   .000259   -1.26   0.207  -.000835   .000181     221.9
      medinc | -.000842   .000611   -1.38   0.168  -.002041   .000356     58.61
   c_citizen | -.016189   .022298   -0.73   0.468  -.059892   .027514    .98607
     c_white |  .001244   .011263    0.11   0.912   -.02083   .023318    .61483
     c_black |  .036843   .022199    1.66   0.097  -.006666   .080352    .11272
  c_hispanic |   .02079    .01656    1.26   0.209  -.011668   .053247    .17183
     c_asian | -.011826   .021098   -0.56   0.575  -.053177   .029526   .041655
    f_income | -.011337   .006793   -1.67   0.095  -.024652   .001977    2.6849
       p_edu | -.003489   .004625   -0.75   0.451  -.012555   .005576    2.4118
    f_single |  .012729   .008997    1.41   0.157  -.004905   .030363    .23923
      f_size |  .005447   .004025    1.35   0.176  -.002442   .013337    4.5348
    language |  .003497   .010937    0.32   0.749  -.017939   .024934    .11061
  c_siblings | -.003702   .003949   -0.94   0.349  -.011441   .004038    1.4813
f_below_po~y |  .020643   .012854    1.61   0.108  -.004551   .045837    .21545
      f_food | -.000421   .005248   -0.08   0.936  -.010707   .009865    1.1354
f_wic_preg~t |  .012495   .010742    1.16   0.245   -.00856    .03355    .39291
 f_wic_child |  .022836   .014827    1.54   0.124  -.006224   .051896    .43428
 f_food_stamp | -.004215   .009225   -0.46   0.648  -.022295   .013864    .05615
 f_religious |  .005927   .005967    0.99   0.321  -.005768   .017623    .57895
m_age_firs~h | -.000913   .000736   -1.24   0.215  -.002356    .00053    24.691
m_married_~h | -.014276   .009288   -1.54   0.124  -.032481   .003929    .71967
  1.f_region | -.018945   .030945   -0.61   0.540  -.079597   .041707         0
  2.f_locale |   .00556   .008822    0.63   0.529  -.011731   .022851         1
  c_age_prek |  .000138   .000554    0.25   0.804  -.000948   .001224    54.471
    c_female | -.001327   .004776   -0.28   0.781  -.010688   .008033    .48508
  c_lowbirth |  .011473   .010625    1.08   0.280  -.009352   .032299   .082043
   c_preterm | -.004096   .006772   -0.60   0.545  -.017369   .009177    .20419
 c_breastfed | -.004103   .005726   -0.72   0.474  -.015326    .00712    .71264
    c_iep_pk |  .032157   .019688    1.63   0.102  -.006431   .070745   .033634
      c_twin |  .016035   .043455    0.37   0.712  -.069135   .101206   .002674
 c_birth_cpl |   .00096   .006857    0.14   0.889   -.01248   .014401    .13932
c_first_w~15 |  .001445   .006055    0.24   0.811  -.010423   .013314    .22699
c_first_s~15 | -.005879   .010236   -0.57   0.566  -.025942   .014183   .072615
     4.state |   -.0352   .020524   -1.72   0.086  -.075427   .005027         1
------------------------------------------------------------------------------
dp/dx for factor levels is the discrete change from the base level

Pr(choice = non-relative|1 selected) = .10393485
------------------------------------------------------------------------------
variable     |   dp/dx   Std. Err.    z     P>|z|  [    95% C.I.    ]       X
-------------+----------------------------------------------------------------
num          |
      center | -.002269   .000979   -2.32   0.021  -.004189   -.00035     3.125
  head_start | -.000272   .000184   -1.48   0.138  -.000632   .000088    .48437
non_relative |  .004626   .001842    2.51   0.012   .001016   .008236    .21544
    parental | -.000385   .000247   -1.56   0.119  -.000868   .000099    .19631
    relative | -.000334   .000219   -1.53   0.127  -.000763   .000095    .12778
 state_pre_K | -.001366   .000643   -2.13   0.034  -.002626  -.000106     1.298
-------------+----------------------------------------------------------------
casevars     |
 p_immigrant | -.006243   .019319   -0.32   0.747  -.044108   .031622      .198
avg_pct_5_~i | -.000901   .000734   -1.23   0.220   -.00234   .000538    64.724
avg_pct_fo~i |  .000092   .000118    0.78   0.437   -.00014   .000323    98.667
avg_pct_ra~i | -.000325    .00025   -1.30   0.193  -.000814   .000164    136.87
avg_pct_fe~i |  .000273   .000367    0.74   0.457  -.000446   .000993     221.9
```

medinc	-.00136	.000948	-1.43	0.151	-.003218	.000498	58.61
c_citizen	-.021003	.051869	-0.40	0.686	-.122665	.080659	.98607
c_white	.081486	.040785	2.00	0.046	.001549	.161423	.61483
c_black	.056271	.040683	1.38	0.167	-.023465	.136007	.11272
c_hispanic	.094853	.047352	2.00	0.045	.002046	.187661	.17183
c_asian	-.073679	.06286	-1.17	0.241	-.196883	.049524	.041655
f_income	.016234	.009507	1.71	0.088	-.002399	.034866	2.6849
p_edu	.011682	.008547	1.37	0.172	-.00507	.028433	2.4118
f_single	.007616	.015972	0.48	0.633	-.023688	.038921	.23923
f_size	-.004973	.009822	-0.51	0.613	-.024224	.014278	4.5348
language	-.005226	.030816	-0.17	0.865	-.065624	.055173	.11061
c_siblings	-.00925	.011058	-0.84	0.403	-.030922	.012422	1.4813
f_below_po~y	-.012973	.021726	-0.60	0.550	-.055554	.029609	.21545
f_food	.017263	.014982	1.15	0.249	-.012102	.046628	1.1354
f_wic_preg~t	.015114	.02102	0.72	0.472	-.026085	.056313	.39291
f_wic_child	-.037389	.025443	-1.47	0.142	-.087255	.012478	.43428
f_food_stamp	.024641	.023786	1.04	0.300	-.021979	.071261	.05615
f_religious	-.013505	.010927	-1.24	0.216	-.034921	.007911	.57895
m_age_firs~h	-.000591	.001125	-0.53	0.599	-.002797	.001614	24.691
m_married_~h	-.005636	.014895	-0.38	0.705	-.034829	.023557	.71967
1.f_region	-.043869	.047428	-0.92	0.355	-.136827	.049088	0
2.f_locale	-.019115	.017189	-1.11	0.266	-.052805	.014575	1
c_age_prek	-.00147	.001208	-1.22	0.224	-.003839	.000898	54.471
c_female	.008274	.009575	0.86	0.387	-.010492	.027041	.48508
c_lowbirth	-.016183	.020665	-0.78	0.434	-.056686	.02432	.082043
c_preterm	.025755	.015786	1.63	0.103	-.005185	.056696	.20419
c_breastfed	.009731	.011888	0.82	0.413	-.013568	.033031	.71264
c_iep_pk	-.023667	.031333	-0.76	0.450	-.085078	.037745	.033634
c_twin	-.02601	.103698	-0.25	0.802	-.229255	.177234	.002674
c_birth_cpl	.011411	.013683	0.83	0.404	-.015407	.03823	.13932
c_first_w~15	.00553	.011578	0.48	0.633	-.017162	.028222	.22699
c_first_s~15	.002003	.019203	0.10	0.917	-.035634	.03964	.072615
4.state	-.025835	.036305	-0.71	0.477	-.096992	.045322	1

dp/dx for factor levels is the discrete change from the base level

Pr(choice = parental|1 selected) = .07449074

variable	dp/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
num							
center	-.001626	.000803	-2.03	0.043	-.0032	-.000053	3.125
head_start	-.000195	.000144	-1.35	0.176	-.000477	.000087	.48437
non_relative	-.000385	.000247	-1.56	0.119	-.000868	.000099	.21544
parental	.003424	.001631	2.10	0.036	.000228	.006621	.19631
relative	-.000239	.000171	-1.40	0.160	-.000574	.000095	.12778
state_pre_K	-.000979	.00054	-1.81	0.070	-.002037	.000079	1.298
casevars							
p_immigrant	.023013	.013322	1.73	0.084	-.003098	.049124	.198
avg_pct_5_~i	.000021	.000279	0.08	0.940	-.000526	.000568	64.724
avg_pct_fo~i	.000159	.000086	1.86	0.064	-9.0e-06	.000327	98.667
avg_pct_ra~i	.000043	.000091	0.47	0.636	-.000135	.000221	136.87
avg_pct_fe~i	.00006	.000174	0.34	0.731	-.000282	.000401	221.9
medinc	-.000286	.000395	-0.72	0.469	-.001061	.000488	58.61
c_citizen	-.042336	.02549	-1.66	0.097	-.092294	.007623	.98607
c_white	-.011843	.011779	-1.01	0.315	-.034929	.011243	.61483
c_black	-.012619	.013976	-0.90	0.367	-.040011	.014773	.11272
c_hispanic	-.018057	.014854	-1.22	0.224	-.04717	.011056	.17183
c_asian	-.015074	.017545	-0.86	0.390	-.049462	.019313	.041655
f_income	-.024039	.011488	-2.09	0.036	-.046554	-.001523	2.6849
p_edu	-.026272	.012678	-2.07	0.038	-.051121	-.001423	2.4118
f_single	-.028654	.015031	-1.91	0.057	-.058114	.000805	.23923
f_size	.009578	.005562	1.72	0.085	-.001325	.02048	4.5348
language	.016342	.012713	1.29	0.199	-.008574	.041259	.11061
c_siblings	.009028	.005685	1.59	0.112	-.002114	.02017	1.4813
f_below_po~y	.002487	.008009	0.31	0.756	-.013211	.018184	.21545
f_food	-.00131	.005553	-0.24	0.813	-.012195	.009574	1.1354
f_wic_preg~t	.00708	.009619	0.74	0.462	-.011773	.025932	.39291
f_wic_child	-.013569	.01201	-1.13	0.259	-.037109	.00997	.43428
f_food_stamp	.000142	.009988	0.01	0.989	-.019435	.019719	.05615

f_religious	-.011149	.006953	-1.60	0.109	-.024777	.002478	.57895
m_age_firs~h	-.000727	.00065	-1.12	0.263	-.002001	.000547	24.691
m_married_~h	-.005751	.006812	-0.84	0.399	-.019102	.0076	.71967
1.f_region	.04026	.045665	0.88	0.378	-.049241	.129762	0
2.f_locale	-.005875	.007575	-0.78	0.438	-.020721	.008972	1
c_age_prek	-.000404	.000563	-0.72	0.472	-.001507	.000698	54.471
c_female	.004111	.004925	0.83	0.404	-.005541	.013763	.48508
c_lowbirth	.002234	.009453	0.24	0.813	-.016295	.020762	.082043
c_preterm	-.011966	.008481	-1.41	0.158	-.028589	.004657	.20419
c_breastfed	-.012205	.007753	-1.57	0.115	-.0274	.002991	.71264
c_iep_pk	.012063	.015957	0.76	0.450	-.019213	.043339	.033634
c_twin	-.010028	.047626	-0.21	0.833	-.103373	.083318	.002674
c_birth_cpl	-.000103	.00687	-0.01	0.988	-.013568	.013363	.13932
c_first_w~15	.004128	.005913	0.70	0.485	-.007461	.015718	.22699
c_first_s~15	.010438	.010194	1.02	0.306	-.009542	.030418	.072615
4.state	-.036702	.020746	-1.77	0.077	-.077364	.00396	1

dp/dx for factor levels is the discrete change from the base level

Pr(choice = relative|1 selected) = .06471662

variable	dp/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
num							
center	-.001413	.000719	-1.96	0.049	-.002823	-3.4e-06	3.125
head_start	-.000169	.000127	-1.34	0.181	-.000418	.000079	.48437
non_relative	-.000334	.000219	-1.53	0.127	-.000763	.000095	.21544
parental	-.000239	.000171	-1.40	0.160	-.000574	.000095	.19631
relative	.003007	.001473	2.04	0.041	.000119	.005895	.12778
state_pre_K	-.000851	.000477	-1.78	0.075	-.001786	.000084	1.298
casevars							
p_immigrant	.011954	.010204	1.17	0.241	-.008045	.031954	.198
avg_pct_5_~i	.000267	.000313	0.85	0.394	-.000347	.00088	64.724
avg_pct_fo~i	.000089	.000061	1.46	0.143	-.00003	.000209	98.667
avg_pct_ra~i	-.000026	.000092	-0.29	0.773	-.000207	.000154	136.87
avg_pct_fe~i	-.000089	.000183	-0.48	0.629	-.000448	.000271	221.9
medinc	-.000786	.000525	-1.50	0.134	-.001814	.000242	58.61
c_citizen	.010911	.023697	0.46	0.645	-.035534	.057357	.98607
c_white	-.001736	.010735	-0.16	0.872	-.022777	.019305	.61483
c_black	-.000452	.012745	-0.04	0.972	-.025433	.024528	.11272
c_hispanic	.007805	.012883	0.61	0.545	-.017445	.033054	.17183
c_asian	.004787	.016878	0.28	0.777	-.028293	.037868	.041655
f_income	-.000837	.003642	-0.23	0.818	-.007976	.006302	2.6849
p_edu	-.01445	.007851	-1.84	0.066	-.029839	.000938	2.4118
f_single	.046211	.022857	2.02	0.043	.001412	.091011	.23923
f_size	.018254	.009145	2.00	0.046	.00033	.036178	4.5348
language	.011918	.01223	0.97	0.330	-.012053	.035888	.11061
c_siblings	-.016545	.008592	-1.93	0.054	-.033386	.000296	1.4813
f_below_po~y	-.009931	.00944	-1.05	0.293	-.028433	.008571	.21545
f_food	.00577	.006294	0.92	0.359	-.006566	.018105	1.1354
f_wic_preg~t	.016368	.012258	1.34	0.182	-.007657	.040393	.39291
f_wic_child	-.018056	.013607	-1.33	0.185	-.044725	.008614	.43428
f_food_stamp	.006499	.009974	0.65	0.515	-.013049	.026048	.05615
f_religious	-.00934	.006453	-1.45	0.148	-.021989	.003308	.57895
m_age_firs~h	-.001212	.000793	-1.53	0.126	-.002767	.000343	24.691
m_married_~h	.006753	.007236	0.93	0.351	-.007429	.020936	.71967
1.f_region	.056957	.043046	1.32	0.186	-.027412	.141326	0
2.f_locale	.011381	.009636	1.18	0.238	-.007505	.030266	1
c_age_prek	-.000089	.000529	-0.17	0.867	-.001125	.000948	54.471
c_female	.00474	.005071	0.93	0.350	-.005199	.01468	.48508
c_lowbirth	.011238	.010593	1.06	0.289	-.009523	.031999	.082043
c_preterm	-.007554	.007328	-1.03	0.303	-.021917	.00681	.20419
c_breastfed	-.014174	.008538	-1.66	0.097	-.030908	.002559	.71264
c_iep_pk	.001552	.014596	0.11	0.915	-.027055	.030159	.033634
c_twin	.006538	.047096	0.14	0.890	-.085768	.098844	.002674
c_birth_cpl	-.002333	.006903	-0.34	0.735	-.015863	.011197	.13932
c_first_w~15	.003884	.005968	0.65	0.515	-.007812	.01558	.22699
c_first_s~15	.011229	.010303	1.09	0.276	-.008965	.031422	.072615
4.state	.045767	.043293	1.06	0.290	-.039087	.13062	1

dp/dx for factor levels is the discrete change from the base level

Pr(choice = state pre-K|1 selected) = .26459914

variable	dp/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
num							
center	-.005777	.001326	-4.36	0.000	-.008376	-.003179	3.125
head_start	-.000693	.000413	-1.68	0.093	-.001501	.000116	.48437
non_relative	-.001366	.000643	-2.13	0.034	-.002626	-.000106	.21544
parental	-.000979	.00054	-1.81	0.070	-.002037	.000079	.19631
relative	-.000851	.000477	-1.78	0.075	-.001786	.000084	.12778
state_pre_K	.009665	.001901	5.08	0.000	.00594	.013391	1.298
casevars							
p_immigrant	.025442	.024458	1.04	0.298	-.022495	.073379	.198
avg_pct_5_~i	.000768	.00082	0.94	0.349	-.000839	.002374	64.724
avg_pct_fo~i	-.000366	.00014	-2.61	0.009	-.000641	-.000091	98.667
avg_pct_ra~i	.000605	.000265	2.28	0.023	.000085	.001126	136.87
avg_pct_fe~i	.000402	.000483	0.83	0.404	-.000543	.001348	221.9
medinc	-.000127	.001055	-0.12	0.904	-.002194	.00194	58.61
c_citizen	.033518	.06302	0.53	0.595	-.089999	.157034	.98607
c_white	-.044809	.031712	-1.41	0.158	-.106962	.017345	.61483
c_black	.020792	.036595	0.57	0.570	-.050933	.092517	.11272
c_hispanic	.012463	.03637	0.34	0.732	-.058821	.083747	.17183
c_asian	.019939	.048553	0.41	0.681	-.075224	.115102	.041655
f_income	-.032872	.011736	-2.80	0.005	-.055874	-.00987	2.6849
p_edu	-.011691	.011706	-1.00	0.318	-.034635	.011252	2.4118
f_single	-.020968	.021221	-0.99	0.323	-.062561	.020624	.23923
f_size	.015021	.0112	1.34	0.180	-.006929	.036972	4.5348
language	.051185	.031997	1.60	0.110	-.011528	.113898	.11061
c_siblings	.001421	.012124	0.12	0.907	-.022342	.025183	1.4813
f_below_po~y	.025576	.024335	1.05	0.293	-.022119	.073271	.21545
f_food	-.018278	.017789	-1.03	0.304	-.053144	.016588	1.1354
f_wic_preg~t	-.01154	.026376	-0.44	0.662	-.063236	.040157	.39291
f_wic_child	.122677	.032619	3.76	0.000	.058744	.18661	.43428
f_food_stamp	-.005192	.028764	-0.18	0.857	-.061568	.051183	.05615
f_religious	.006811	.014245	0.48	0.633	-.021109	.034732	.57895
m_age_firs~h	-.00321	.001652	-1.94	0.052	-.006448	.000027	24.691
m_married_~h	-.004093	.018713	-0.22	0.827	-.04077	.032584	.71967
1.f_region	.060042	.07758	0.77	0.439	-.092012	.212097	0
2.f_locale	-.031566	.020859	-1.51	0.130	-.072449	.009317	1
c_age_prek	.004473	.001634	2.74	0.006	.00127	.007676	54.471
c_female	-.020639	.013494	-1.53	0.126	-.047086	.005808	.48508
c_lowbirth	-.015843	.026727	-0.59	0.553	-.068228	.036542	.082043
c_preterm	.009728	.017978	0.54	0.588	-.025508	.044964	.20419
c_breastfed	-.012585	.01561	-0.81	0.420	-.04318	.01801	.71264
c_iep_pk	.211481	.047743	4.43	0.000	.117906	.305056	.033634
c_twin	-.016515	.134201	-0.12	0.902	-.279545	.246515	.002674
c_birth_cpl	.024452	.019183	1.27	0.202	-.013146	.06205	.13932
c_first_w~15	.023381	.016457	1.42	0.155	-.008874	.055636	.22699
c_first_s~15	.051029	.026391	1.93	0.053	-.000696	.102755	.072615
4.state	.131153	.083745	1.57	0.117	-.032985	.295291	1

dp/dx for factor levels is the discrete change from the base level

Table C. 2 Stata outputs of marginal effects: 10-mile model

Equation Name	Alternative
center	center
head_start	head start
non_relative	non-relative
parental	parental
relative	relative
state_pre_K	state pre-K

Pr(choice = center|1 selected) = .40852481

variable	dp/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
num							
center	.001868	.00046	4.06	0.000	.000966	.00277	13.509
head_start	-.000159	.000092	-1.73	0.084	-.000339	.000021	1.4095
non_relative	-.000312	.000154	-2.03	0.042	-.000613	-.000011	.73425
parental	-.000238	.000129	-1.85	0.064	-.00049	.000014	.19631
relative	-.000206	.000115	-1.80	0.072	-.000431	.000018	.12778
state_pre_K	-.000952	.000289	-3.29	0.001	-.00152	-.000385	3.8472
casevars							
p_immigrant	-.065489	.028223	-2.32	0.020	-.120805	-.010173	.198
avg_pct_5_~i	-.0013	.001299	-1.00	0.317	-.003847	.001246	64.201
avg_pct_fo~i	.000038	.000197	0.19	0.847	-.000348	.000424	100.62
avg_pct_ra~i	.00011	.0004	0.27	0.784	-.000675	.000894	138.24
avg_pct_fe~i	.001245	.000704	1.77	0.077	-.000135	.002625	222.17
medinc	.003785	.001454	2.60	0.009	.000935	.006635	58.256
c_citizen	.019654	.071457	0.28	0.783	-.1204	.159707	.98607
c_white	-.019461	.037658	-0.52	0.605	-.093269	.054348	.61483
c_black	-.087122	.04407	-1.98	0.048	-.173498	-.000745	.11272
c_hispanic	-.11577	.043878	-2.64	0.008	-.201769	-.029771	.17183
c_asian	.071339	.056016	1.27	0.203	-.03845	.181129	.041655
f_income	.051441	.012775	4.03	0.000	.026402	.07648	2.6849
p_edu	.044487	.012986	3.43	0.001	.019036	.069938	2.4118
f_single	-.013966	.026998	-0.52	0.605	-.066881	.038949	.23923
f_size	-.040475	.014663	-2.76	0.006	-.069213	-.011737	4.5348
language	-.085657	.040253	-2.13	0.033	-.164551	-.006763	.11061
c_siblings	.01744	.016285	1.07	0.284	-.014478	.049357	1.4813
f_below_po~y	-.022777	.031876	-0.71	0.475	-.085253	.039699	.21545
f_food	-.00409	.022737	-0.18	0.857	-.048653	.040472	1.1354
f_wic_preg~t	-.027766	.033196	-0.84	0.403	-.092829	.037297	.39291
f_wic_child	-.084681	.036842	-2.30	0.022	-.15689	-.012473	.43428
f_food_stamp	-.017458	.037182	-0.47	0.639	-.090333	.055418	.05615
f_religious	.018985	.0164	1.16	0.247	-.013158	.051127	.57895
m_age_firs~h	.006602	.001742	3.79	0.000	.003188	.010015	24.691
m_married_~h	.020895	.023389	0.89	0.372	-.024947	.066737	.71967
1.f_region	-.101417	.087495	-1.16	0.246	-.272903	.07007	0
2.f_locale	.029231	.024171	1.21	0.227	-.018143	.076606	1
c_age_prek	-.002478	.001759	-1.41	0.159	-.005927	.00097	54.471
c_female	.00475	.015056	0.32	0.752	-.024759	.034258	.48508
c_lowbirth	.010114	.03106	0.33	0.745	-.050763	.070992	.082043
c_preterm	-.009176	.021049	-0.44	0.663	-.05043	.032079	.20419
c_breastfed	.033204	.018171	1.83	0.068	-.00241	.068817	.71264
c_iep_pk	-.240907	.056259	-4.28	0.000	-.351173	-.130641	.033634
c_twin	.041283	.134526	0.31	0.759	-.222383	.30495	.002674
c_birth_cpl	-.032823	.022092	-1.49	0.137	-.076123	.010478	.13932
c_first_w~15	-.042252	.018754	-2.25	0.024	-.079009	-.005495	.22699
c_first_s~15	-.064765	.031518	-2.05	0.040	-.126539	-.002992	.072615
4.state	-.016444	.07882	-0.21	0.835	-.170929	.138041	1

dp/dx for factor levels is the discrete change from the base level

Pr(choice = head start|1 selected) = .05036126

variable	dp/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X

```
num          |
      center | -.000159   .000092   -1.73   0.084  -.000339   .000021    13.509
  head_start |   .00037   .000208    1.78   0.076  -.000039   .000778    1.4095
non_relative | -.000038   .000027   -1.41   0.160  -.000092   .000015    .73425
    parental | -.000029   .000022   -1.30   0.192  -.000073   .000015    .19631
    relative | -.000025    .00002   -1.29   0.197  -.000064   .000013    .12778
 state_pre_K | -.000117   .000073   -1.60   0.109  -.000261   .000026    3.8472
-------------+-------------------------------------------------------------------
casevars     |
 p_immigrant |  .015145   .011415    1.33   0.185  -.007228   .037518      .198
avg_pct_5_~i | -.000616   .000479   -1.29   0.199  -.001555   .000323    64.201
avg_pct_fo~i |  .000137   .000083    1.64   0.101  -.000027     .0003    100.62
avg_pct_ra~i | -2.9e-06   .000115   -0.03   0.980  -.000228   .000222    138.24
avg_pct_fe~i | -.000523   .000348   -1.50   0.133  -.001206   .000159    222.17
      medinc | -.000662   .000608   -1.09   0.276  -.001853   .000529    58.256
   c_citizen | -.013637   .021045   -0.65   0.517  -.054884   .027609    .98607
     c_white |  .002103   .010802    0.19   0.846  -.019068   .023274    .61483
     c_black |  .033151   .020266    1.64   0.102   -.00657   .072871    .11272
  c_hispanic |  .019499   .015659    1.25   0.213  -.011192   .050191    .17183
     c_asian | -.010527   .019988   -0.53   0.598  -.049701   .028648   .041655
    f_income | -.010486   .006343   -1.65   0.098  -.022919   .001946    2.6849
       p_edu | -.003571   .004483   -0.80   0.426  -.012358   .005215    2.4118
    f_single |  .012142   .008573    1.42   0.157  -.004661   .028944    .23923
      f_size |  .004704   .003663    1.28   0.199  -.002476   .011884    4.5348
    language |  .004268   .010475    0.41   0.684  -.016263   .024799    .11061
  c_siblings |  -.00349   .003738   -0.93   0.351  -.010817   .003838    1.4813
f_below_po~y |  .018803   .011869    1.58   0.113   -.00446   .042065    .21545
      f_food |  .000022   .004989    0.00   0.996  -.009757   .009801    1.1354
f_wic_preg~t |  .010753   .009944    1.08   0.280  -.008736   .030242    .39291
 f_wic_child |  .021486   .014089    1.52   0.127  -.006128     .0491    .43428
f_food_stamp | -.004035   .008778   -0.46   0.646  -.021241    .01317    .05615
 f_religious |  .005893   .005762    1.02   0.306  -.005401   .017187    .57895
m_age_firs~h | -.000852   .000697   -1.22   0.222  -.002219   .000514    24.691
m_married_~h | -.013441   .008777   -1.53   0.126  -.030644   .003763    .71967
  1.f_region | -.016771   .029596   -0.57   0.571  -.074777   .041236         0
  2.f_locale |  .003849   .007964    0.48   0.629  -.011759   .019458         1
  c_age_prek |  .000094   .000529    0.18   0.860  -.000943    .00113    54.471
    c_female | -.000916   .004542   -0.20   0.840  -.009818   .007987    .48508
  c_lowbirth |  .011272   .010199    1.11   0.269  -.008719   .031262   .082043
   c_preterm | -.004207   .006517   -0.65   0.519   -.01698   .008566    .20419
 c_breastfed | -.003548   .005398   -0.66   0.511  -.014128   .007031    .71264
    c_iep_pk |  .029171   .018269    1.60   0.110  -.006636   .064977   .033634
      c_twin |   .01486    .04127    0.36   0.719  -.066027   .095747   .002674
 c_birth_cpl |  .001282   .006569    0.20   0.845  -.011593   .014156    .13932
c_first_w~15 |  .001657   .005806    0.29   0.775  -.009722   .013035    .22699
c_first_s~15 | -.006788   .009961   -0.68   0.496   -.02631   .012735   .072615
     4.state | -.031878   .018918   -1.69   0.092  -.068957     .0052         1
---------------------------------------------------------------------------------
dp/dx for factor levels is the discrete change from the base level

Pr(choice = non-relative|1 selected) =  .0988871
---------------------------------------------------------------------------------
variable     |   dp/dx   Std. Err.    z     P>|z|  [    95% C.I.    ]       X
-------------+-------------------------------------------------------------------
num          |
      center | -.000312   .000154   -2.03   0.042  -.000613  -.000011    13.509
  head_start | -.000038   .000027   -1.41   0.160  -.000092   .000015    1.4095
non_relative |  .000689   .000315    2.19   0.029   .000071   .001306    .73425
    parental | -.000058   .000039   -1.47   0.141  -.000134   .000019    .19631
    relative |  -.00005   .000035   -1.45   0.148  -.000118   .000018    .12778
 state_pre_K | -.000231   .000118   -1.95   0.051  -.000462   6.9e-07    3.8472
-------------+-------------------------------------------------------------------
casevars     |
 p_immigrant | -.006806   .018449   -0.37   0.712  -.042965   .029353      .198
avg_pct_5_~i |  -.00074   .000854   -0.87   0.386  -.002413   .000934    64.201
avg_pct_fo~i |  .000122   .000131    0.93   0.351  -.000134   .000378    100.62
avg_pct_ra~i | -.000372   .000294   -1.27   0.205  -.000948   .000203    138.24
avg_pct_fe~i |  .000041   .000433    0.09   0.924  -.000807   .000889    222.17
      medinc | -.001379   .001077   -1.28   0.201   -.00349   .000732    58.256
   c_citizen | -.016314   .049523   -0.33   0.742  -.113377    .08075    .98607
     c_white |  .080103   .039821    2.01   0.044   .002055    .15815    .61483
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```
     c_black |  .050632   .038328    1.32   0.186  -.024489   .125754    .11272
  c_hispanic |  .088545   .044904    1.97   0.049   .000535   .176554    .17183
     c_asian | -.070419   .060146   -1.17   0.242  -.188302   .047464   .041655
    f_income |    .0162   .009248    1.75   0.080  -.001926   .034325    2.6849
       p_edu |  .012318   .008408    1.47   0.143  -.004161   .028798    2.4118
    f_single |  .006584   .015218    0.43   0.665  -.023242    .03641    .23923
      f_size | -.005568   .009411   -0.59   0.554  -.024013   .012876    4.5348
    language | -.006957   .029371   -0.24   0.813  -.064523    .05061    .11061
  c_siblings | -.008587   .010528   -0.82   0.415  -.029222   .012047    1.4813
f_below_po~y | -.014761   .020923   -0.71   0.481   -.05577   .026248    .21545
      f_food |   .01696   .014405    1.18   0.239  -.011273   .045193    1.1354
f_wic_preg~t |  .013382   .020064    0.67   0.505  -.025942   .052706    .39291
 f_wic_child | -.037597   .024818   -1.51   0.130  -.086241   .011046    .43428
f_food_stamp |  .023132   .022681    1.02   0.308  -.021322   .067587    .05615
 f_religious | -.012178   .010358   -1.18   0.240  -.032479   .008123    .57895
m_age_firs~h |  -.00052   .001074   -0.48   0.628  -.002626   .001585    24.691
m_married_~h |  -.00532   .014228   -0.37   0.708  -.033206   .022565    .71967
  1.f_region |  -.04089    .04523   -0.90   0.366  -.129539   .047759         0
  2.f_locale |  -.01209   .015542   -0.78   0.437  -.042551   .018372         1
  c_age_prek |  -.00153   .001179   -1.30   0.194   -.00384    .00078    54.471
    c_female |  .008372    .00922    0.91   0.364  -.009699   .026443    .48508
  c_lowbirth | -.016664   .019922   -0.84   0.403  -.055711   .022382   .082043
   c_preterm |  .024938   .015224    1.64   0.101  -.004902   .054777    .20419
 c_breastfed |  .009676   .011401    0.85   0.396  -.012669   .032021    .71264
    c_iep_pk | -.025889    .03026   -0.86   0.392  -.085198    .03342   .033634
      c_twin | -.027842   .099848   -0.28   0.780  -.223541   .167857   .002674
 c_birth_cpl |  .010376   .013046    0.80   0.426  -.015193   .035945    .13932
c_first_w~15 |  .005366   .011105    0.48   0.629  -.016399   .027131    .22699
c_first_s~15 |  .000525   .018315    0.03   0.977  -.035372   .036422   .072615
     4.state | -.035747   .032033   -1.12   0.264   -.09853   .027036         1
-------------------------------------------------------------------------------
dp/dx for factor levels is the discrete change from the base level

Pr(choice = parental|1 selected) = .07532016
-------------------------------------------------------------------------------
variable     |   dp/dx   Std. Err.    z     P>|z|  [    95% C.I.    ]       X
-------------+-----------------------------------------------------------------
num          |
      center | -.000238   .000129   -1.85   0.064   -.00049   .000014    13.509
  head_start | -.000029   .000022   -1.30   0.192  -.000073   .000015    1.4095
non_relative | -.000058   .000039   -1.47   0.141  -.000134   .000019    .73425
    parental |  .000538   .000281    1.92   0.055  -.000012   .001089    .19631
    relative | -.000038   .000028   -1.35   0.177  -.000093   .000017    .12778
 state_pre_K | -.000176   .000102   -1.72   0.085  -.000375   .000024    3.8472
-------------+-----------------------------------------------------------------
casevars     |
 p_immigrant |  .022829   .013249    1.72   0.085  -.003138   .048796      .198
avg_pct_5_~i |  .000559   .000455    1.23   0.219  -.000333    .00145    64.201
avg_pct_fo~i |  .000175   .000096    1.82   0.068  -.000013   .000363    100.62
avg_pct_ra~i | -.000095   .000123   -0.77   0.442  -.000336   .000147    138.24
avg_pct_fe~i | -.000098   .000221   -0.45   0.656  -.000531   .000334    222.17
      medinc | -.000521   .000529   -0.99   0.325  -.001559   .000516    58.256
   c_citizen | -.041823   .025277   -1.65   0.098  -.091365   .007718    .98607
     c_white |  -.01059   .011548   -0.92   0.359  -.033223   .012043    .61483
     c_black | -.015298   .014491   -1.06   0.291  -.043699   .013104    .11272
  c_hispanic | -.018224   .014841   -1.23   0.219  -.047312   .010864    .17183
     c_asian | -.013915    .01733   -0.80   0.422  -.047882   .020052   .041655
    f_income | -.023585   .011264   -2.09   0.036  -.045661  -.001508    2.6849
       p_edu | -.026445   .012715   -2.08   0.038  -.051367  -.001524    2.4118
    f_single | -.029377   .015257   -1.93   0.054  -.059281   .000527    .23923
      f_size |  .008854   .005284    1.68   0.094  -.001502   .019211    4.5348
    language |  .016555    .01276    1.30   0.195  -.008455   .041564    .11061
  c_siblings |  .009292   .005731    1.62   0.105   -.00194   .020524    1.4813
f_below_po~y |  .001888   .007948    0.24   0.812   -.01369   .017466    .21545
      f_food | -.000646    .00551   -0.12   0.907  -.011446   .010153    1.1354
f_wic_preg~t |  .005814   .009461    0.61   0.539  -.012729   .024357    .39291
 f_wic_child | -.014582   .012308   -1.18   0.236  -.038704   .009541    .43428
f_food_stamp | -.000431   .010016   -0.04   0.966  -.020061     .0192    .05615
 f_religious | -.011277   .006998   -1.61   0.107  -.024993   .002439    .57895
m_age_firs~h | -.000639   .000635   -1.01   0.314  -.001883   .000605    24.691
m_married_~h | -.005632   .006791   -0.83   0.407  -.018942   .007677    .71967
```

```
  1.f_region |  .036946   .045486    0.81   0.417  -.052205   .126096         0
  2.f_locale | -.004007   .007267   -0.55   0.581   -.01825   .010235         1
  c_age_prek | -.000492   .000579   -0.85   0.396  -.001627   .000644    54.471
    c_female |   .00435   .004988    0.87   0.383  -.005426   .014127    .48508
  c_lowbirth |   .00211   .009475    0.22   0.824  -.016462   .020681   .082043
   c_preterm | -.012275   .008569   -1.43   0.152   -.02907    .00452    .20419
 c_breastfed | -.011777    .00762   -1.55   0.122  -.026711   .003157    .71264
    c_iep_pk |  .009596   .015884    0.60   0.546  -.021536   .040728   .033634
      c_twin | -.011613    .04812   -0.24   0.809  -.105926   .082699   .002674
 c_birth_cpl | -.000566   .006912   -0.08   0.935  -.014113   .012982    .13932
c_first_w~15 |  .004219    .00597    0.71   0.480  -.007482   .015921    .22699
c_first_s~15 |   .00928   .009978    0.93   0.352  -.010276   .028835   .072615
     4.state | -.037317   .020759   -1.80   0.072  -.078004    .00337         1
------------------------------------------------------------------------------
dp/dx for factor levels is the discrete change from the base level

Pr(choice = relative|1 selected) = .06533789
------------------------------------------------------------------------------
variable     |   dp/dx   Std. Err.    z     P>|z|  [    95% C.I.    ]       X
-------------+----------------------------------------------------------------
num          |
      center | -.000206   .000115   -1.80   0.072  -.000431   .000018    13.509
  head_start | -.000025    .00002   -1.29   0.197  -.000064   .000013    1.4095
non_relative |  -.00005   .000035   -1.45   0.148  -.000118   .000018    .73425
    parental | -.000038   .000028   -1.35   0.177  -.000093   .000017    .19631
    relative |  .000472   .000252    1.87   0.061  -.000022   .000966    .12778
 state_pre_K | -.000152    .00009   -1.70   0.090  -.000328   .000024    3.8472
-------------+----------------------------------------------------------------
casevars     |
 p_immigrant |  .011509   .010115    1.14   0.255  -.008315   .031334      .198
avg_pct_5_~i |  .000635   .000496    1.28   0.200  -.000336   .001607    64.201
avg_pct_fo~i |  .000041   .000057    0.72   0.474  -.000071   .000153    100.62
avg_pct_ra~i | -.000034   .000119   -0.29   0.776  -.000267   .000199    138.24
avg_pct_fe~i |  .000044   .000216    0.20   0.838   -.00038   .000468    222.17
      medinc | -.000819    .00061   -1.34   0.179  -.002015   .000377    58.256
   c_citizen |  .012134   .023977    0.51   0.613  -.034859   .059127    .98607
     c_white | -.000597   .010745   -0.06   0.956  -.021656   .020463    .61483
     c_black | -.003217   .012843   -0.25   0.802  -.028389   .021955    .11272
  c_hispanic |  .009507   .013125    0.72   0.469  -.016218   .035231    .17183
     c_asian |  .005854   .016972    0.34   0.730  -.027411   .039119   .041655
    f_income | -.000345   .003637   -0.09   0.924  -.007473   .006784    2.6849
       p_edu | -.014652   .007928   -1.85   0.065  -.030189   .000886    2.4118
    f_single |  .046952   .023052    2.04   0.042   .001772   .092132    .23923
      f_size |  .017958   .008969    2.00   0.045    .00038   .035536    4.5348
    language |  .012549   .012393    1.01   0.311  -.011742   .036839    .11061
  c_siblings | -.016845   .008667   -1.94   0.052  -.033833   .000142    1.4813
f_below_po~y |  -.01088   .009629   -1.13   0.258  -.029752   .007991    .21545
      f_food |   .00609    .00634    0.96   0.337  -.006336   .018517    1.1354
f_wic_preg~t |  .015918    .01213    1.31   0.189  -.007857   .039693    .39291
 f_wic_child | -.018693     .0138   -1.35   0.176   -.04574   .008353    .43428
f_food_stamp |  .006579   .009988    0.66   0.510  -.012998   .026155    .05615
 f_religious |  -.00963   .006555   -1.47   0.142  -.022477   .003218    .57895
m_age_firs~h | -.001195    .00079   -1.51   0.130  -.002743   .000352    24.691
m_married_~h |  .007483   .007406    1.01   0.312  -.007032   .021998    .71967
  1.f_region |   .05523   .043028    1.28   0.199  -.029103   .139563         0
  2.f_locale |  .014194   .010315    1.38   0.169  -.006023   .034412         1
  c_age_prek | -.000159   .000536   -0.30   0.767   -.00121   .000892    54.471
    c_female |  .005068   .005156    0.98   0.326  -.005038   .015173    .48508
  c_lowbirth |  .010763   .010494    1.03   0.305  -.009804    .03133   .082043
   c_preterm | -.007727   .007394   -1.05   0.296  -.022219   .006765    .20419
 c_breastfed | -.013999   .008466   -1.65   0.098  -.030591   .002593    .71264
    c_iep_pk | -.000222   .014747   -0.02   0.988  -.029126   .028682   .033634
      c_twin |   .00445   .047381    0.09   0.925  -.088416   .097315   .002674
 c_birth_cpl | -.002432   .006944   -0.35   0.726  -.016041   .011177    .13932
c_first_w~15 |   .00369   .005986    0.62   0.538  -.008042   .015421    .22699
c_first_s~15 |  .010115   .010072    1.00   0.315  -.009626   .029857   .072615
     4.state |  .047355   .043777    1.08   0.279  -.038447   .133157         1
------------------------------------------------------------------------------
dp/dx for factor levels is the discrete change from the base level

Pr(choice = state pre-K|1 selected) = .30156877
```

variable	dp/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
num							
center	-.000952	.000289	-3.29	0.001	-.00152	-.000385	13.509
head_start	-.000117	.000073	-1.60	0.109	-.000261	.000026	1.4095
non_relative	-.000231	.000118	-1.95	0.051	-.000462	6.9e-07	.73425
parental	-.000176	.000102	-1.72	0.085	-.000375	.000024	.19631
relative	-.000152	.00009	-1.70	0.090	-.000328	.000024	.12778
state_pre_K	.001628	.000455	3.58	0.000	.000736	.002521	3.8472
casevars							
p_immigrant	.022812	.026204	0.87	0.384	-.028547	.07417	.198
avg_pct_5_~i	.001462	.001161	1.26	0.208	-.000813	.003737	64.201
avg_pct_fo~i	-.000512	.000172	-2.97	0.003	-.00085	-.000175	100.62
avg_pct_ra~i	.000394	.000352	1.12	0.263	-.000295	.001084	138.24
avg_pct_fe~i	-.000708	.000647	-1.09	0.274	-.001977	.00056	222.17
medinc	-.000404	.001388	-0.29	0.771	-.003124	.002316	58.256
c_citizen	.039986	.067738	0.59	0.555	-.092778	.17275	.98607
c_white	-.051559	.033949	-1.52	0.129	-.118097	.01498	.61483
c_black	.021853	.039114	0.56	0.576	-.05481	.098516	.11272
c_hispanic	.016443	.039137	0.42	0.674	-.060264	.093151	.17183
c_asian	.017668	.052199	0.34	0.735	-.08464	.119976	.041655
f_income	-.033225	.0123	-2.70	0.007	-.057332	-.009117	2.6849
p_edu	-.012137	.012778	-0.95	0.342	-.037181	.012907	2.4118
f_single	-.022335	.02288	-0.98	0.329	-.06718	.022509	.23923
f_size	.014527	.011926	1.22	0.223	-.008847	.037901	4.5348
language	.059242	.034189	1.73	0.083	-.007766	.126251	.11061
c_siblings	.002191	.013031	0.17	0.866	-.02335	.027731	1.4813
f_below_po~y	.027727	.025972	1.07	0.286	-.023177	.078631	.21545
f_food	-.018336	.018986	-0.97	0.334	-.055548	.018876	1.1354
f_wic_preg~t	-.018101	.028267	-0.64	0.522	-.073504	.037301	.39291
f_wic_child	.134068	.033408	4.01	0.000	.06859	.199546	.43428
f_food_stamp	-.007787	.030908	-0.25	0.801	-.068365	.052791	.05615
f_religious	.008207	.015342	0.53	0.593	-.021862	.038277	.57895
m_age_firs~h	-.003395	.001758	-1.93	0.054	-.006842	.000051	24.691
m_married_~h	-.003985	.020102	-0.20	0.843	-.043384	.035414	.71967
1.f_region	.066902	.082657	0.81	0.418	-.095104	.228907	0
2.f_locale	-.031178	.021799	-1.43	0.153	-.073903	.011546	1
c_age_prek	.004565	.001697	2.69	0.007	.001239	.007891	54.471
c_female	-.021625	.014379	-1.50	0.133	-.049807	.006557	.48508
c_lowbirth	-.017594	.028726	-0.61	0.540	-.073897	.038708	.082043
c_preterm	.008447	.019373	0.44	0.663	-.029523	.046417	.20419
c_breastfed	-.013555	.016792	-0.81	0.420	-.046468	.019357	.71264
c_iep_pk	.228251	.047874	4.77	0.000	.134419	.322083	.033634
c_twin	-.021138	.145042	-0.15	0.884	-.305416	.26314	.002674
c_birth_cpl	.024162	.020501	1.18	0.239	-.01602	.064344	.13932
c_first_w~15	.027321	.017672	1.55	0.122	-.007316	.061957	.22699
c_first_s~15	.051633	.027875	1.85	0.064	-.003001	.106267	.072615
4.state	.07403	.081518	0.91	0.364	-.085742	.233803	1

dp/dx for factor levels is the discrete change from the base level

Table C. 3 Stata outputs of marginal effects: 25-minute model

```
Equation Name           Alternative
--------------------------------------------------
center                  center
head_start              head start
non_relative            non-relative
parental                parental
relative                relative
state_pre_K             state pre-K


Pr(choice = center|1 selected) =  .4047849
------------------------------------------------------------------------------
variable     |   dp/dx   Std. Err.    z     P>|z|  [    95% C.I.    ]       X
-------------+----------------------------------------------------------------
num          |
      center |  .006899   .000934    7.39   0.000   .005069   .008729   9.1722
  head_start | -.000652    .00035   -1.86   0.062  -.001338   .000034   1.4407
non_relative | -.001197   .000531   -2.26   0.024  -.002237  -.000157   .75521
    parental | -.000977   .000481   -2.03   0.042  -.001919  -.000035   .19631
    relative |   -.0008    .00041   -1.95   0.051  -.001603   3.2e-06   .12778
 state_pre_K | -.003273   .000775   -4.22   0.000  -.004793  -.001754    4.387
-------------+----------------------------------------------------------------
casevars     |
 p_immigrant | -.072375   .028215   -2.57   0.010  -.127676  -.017074     .198
avg_pct_5_~i |  .000234   .001447    0.16   0.871  -.002601    .00307   64.946
avg_pct_fo~i | -.000264   .000194   -1.36   0.174  -.000644   .000116   101.77
avg_pct_ra~i |  .000408   .000429    0.95   0.342  -.000433   .001248   140.73
avg_pct_fe~i |  .000307   .000749    0.41   0.682  -.001161   .001774   224.03
      medinc |  .006311   .001604    3.93   0.000   .003168   .009455   58.109
   c_citizen |   .02606   .070903    0.37   0.713  -.112908   .165028   .98607
     c_white | -.017985   .037648   -0.48   0.633  -.091774   .055804   .61483
     c_black | -.110155   .044646   -2.47   0.014  -.197659   -.02265   .11272
  c_hispanic | -.112966    .04418   -2.56   0.011  -.199557  -.026374   .17183
     c_asian |  .074851   .055902    1.34   0.181  -.034715   .184417  .041655
    f_income |  .054871   .012971    4.23   0.000   .029448   .080293   2.6849
       p_edu |  .045711    .01309    3.49   0.000   .020056   .071366   2.4118
    f_single | -.014133   .027235   -0.52   0.604  -.067512   .039247   .23923
      f_size | -.041759   .014723   -2.84   0.005  -.070615  -.012903   4.5348
    language | -.080041   .040056   -2.00   0.046   -.15855  -.001532   .11061
  c_siblings |  .017671   .016364    1.08   0.280  -.014402   .049744   1.4813
f_below_po~y | -.022731    .03184   -0.71   0.475  -.085136   .039674   .21545
      f_food | -.004151   .022591   -0.18   0.854  -.048429   .040126   1.1354
f_wic_preg~t | -.031749   .033029   -0.96   0.336  -.096484   .032986   .39291
 f_wic_child | -.077035   .036779   -2.09   0.036   -.14912   -.00495   .43428
f_food_stamp | -.018914   .037061   -0.51   0.610  -.091552   .053723   .05615
 f_religious |  .023147    .01636    1.41   0.157  -.008917   .055211   .57895
m_age_firs~h |  .006679   .001733    3.85   0.000   .003283   .010075   24.691
m_married_~h |  .022565   .023345    0.97   0.334  -.023191    .06832   .71967
  1.f_region | -.048287   .089717   -0.54   0.590  -.224129   .127554        0
  2.f_locale |  .040879   .024011    1.70   0.089  -.006181   .087939        1
  c_age_prek |  -.00257   .001762   -1.46   0.145  -.006023   .000883   54.471
    c_female |  .004472   .014935    0.30   0.765    -.0248   .033743   .48508
  c_lowbirth |  .003266   .030933    0.11   0.916  -.057361   .063893  .082043
   c_preterm | -.008441   .020996   -0.40   0.688  -.049593   .032711   .20419
 c_breastfed |  .034882   .018105    1.93   0.054  -.000603   .070367   .71264
    c_iep_pk | -.229535   .056362   -4.07   0.000  -.340003  -.119067  .033634
      c_twin |  .036544   .133713    0.27   0.785  -.225529   .298617  .002674
 c_birth_cpl |   -.0337   .021959   -1.53   0.125  -.076739   .009339   .13932
c_first_w~15 | -.040927   .018634   -2.20   0.028  -.077449  -.004404   .22699
c_first_s~15 | -.067012   .031477   -2.13   0.033  -.128705  -.005319  .072615
     4.state | -.130147   .068998   -1.89   0.059  -.265382   .005087        1
------------------------------------------------------------------------------
dp/dx for factor levels is the discrete change from the base level

Pr(choice = head start|1 selected) = .05624419
------------------------------------------------------------------------------
variable     |   dp/dx   Std. Err.    z     P>|z|  [    95% C.I.    ]       X
-------------+----------------------------------------------------------------
```

```
num          |
      center | -.000652    .00035   -1.86   0.062  -.001338   .000034    9.1722
  head_start |   .00152   .000786    1.93   0.053   -.00002    .00306    1.4407
non_relative | -.000166   .000111   -1.49   0.135  -.000385   .000052    .75521
    parental | -.000136   .000099   -1.38   0.168  -.000329   .000057    .19631
    relative | -.000111   .000082   -1.35   0.175  -.000272    .00005    .12778
 state_pre_K | -.000455   .000266   -1.71   0.087  -.000976   .000066     4.387
-------------+-------------------------------------------------------------
casevars     |
 p_immigrant |  .017397   .012825    1.36   0.175  -.007739   .042533      .198
avg_pct_5_~i | -.000669   .000575   -1.16   0.244  -.001796   .000458    64.946
avg_pct_fo~i |  .000212   .000118    1.80   0.072  -.000019   .000442    101.77
avg_pct_ra~i | -.000109    .00015   -0.73   0.467  -.000403   .000185    140.73
avg_pct_fe~i | -.000548    .00038   -1.44   0.149  -.001293   .000197    224.03
      medinc | -.001056   .000814   -1.30   0.195  -.002652    .00054    58.109
   c_citizen | -.015109   .023271   -0.65   0.516  -.060719   .030501    .98607
     c_white |  .001315    .01195    0.11   0.912  -.022106   .024737    .61483
     c_black |  .039748   .023635    1.68   0.093  -.006576   .086071    .11272
  c_hispanic |  .020998   .017112    1.23   0.220  -.012542   .054537    .17183
     c_asian | -.013938   .022599   -0.62   0.537  -.058232   .030355   .041655
    f_income |  -.01207   .007178   -1.68   0.093  -.026139      .002    2.6849
       p_edu | -.003738   .004934   -0.76   0.449  -.013409   .005933    2.4118
    f_single |  .013001   .009315    1.40   0.163  -.005257   .031258    .23923
      f_size |  .005249   .004066    1.29   0.197   -.00272   .013218    4.5348
    language |  .003664   .011529    0.32   0.751  -.018933   .026261    .11061
  c_siblings | -.003771   .004125   -0.91   0.361  -.011857   .004315    1.4813
f_below_po~y |  .021024   .013162    1.60   0.110  -.004773   .046822    .21545
      f_food |  .000074   .005534    0.01   0.989  -.010772    .01092    1.1354
f_wic_preg~t |  .012015   .011046    1.09   0.277  -.009636   .033665    .39291
 f_wic_child |  .024507   .015758    1.56   0.120  -.006377   .055391    .43428
f_food_stamp | -.004746   .009767   -0.49   0.627  -.023888   .014397    .05615
 f_religious |  .006078    .00626    0.97   0.332  -.006192   .018347    .57895
m_age_firs~h | -.000952   .000774   -1.23   0.218  -.002469   .000564    24.691
m_married_~h | -.014831   .009654   -1.54   0.124  -.033751    .00409    .71967
  1.f_region | -.028272   .031815   -0.89   0.374  -.090628   .034085         0
  2.f_locale |  .001111   .008398    0.13   0.895  -.015349   .017571         1
  c_age_prek |  .000209   .000592    0.35   0.725  -.000952    .00137    54.471
    c_female | -.001363    .00506   -0.27   0.788   -.01128   .008554    .48508
  c_lowbirth |  .012817   .011357    1.13   0.259  -.009442   .035076   .082043
   c_preterm | -.004535   .007207   -0.63   0.529  -.018661    .00959    .20419
 c_breastfed | -.004836   .006144   -0.79   0.431  -.016879   .007207    .71264
    c_iep_pk |  .032676   .020228    1.62   0.106   -.00697   .072322   .033634
      c_twin |  .015719   .045768    0.34   0.731  -.073985   .105423   .002674
 c_birth_cpl |  .001681   .007304    0.23   0.818  -.012634   .015997    .13932
c_first_w~15 |  .001242   .006406    0.19   0.846  -.011314   .013797    .22699
c_first_s~15 | -.007334   .011017   -0.67   0.506  -.028927   .014258   .072615
     4.state | -.031063   .020128   -1.54   0.123  -.070514   .008388         1
---------------------------------------------------------------------------
dp/dx for factor levels is the discrete change from the base level

Pr(choice = non-relative|1 selected) = .10326274
---------------------------------------------------------------------------
variable     |   dp/dx   Std. Err.    z     P>|z|  [    95% C.I.    ]       X
-------------+-------------------------------------------------------------
num          |
      center | -.001197   .000531   -2.26   0.024  -.002237  -.000157    9.1722
  head_start | -.000166   .000111   -1.49   0.135  -.000385   .000052    1.4407
non_relative |  .002652   .001061    2.50   0.012   .000572   .004732    .75521
    parental | -.000249   .000158   -1.58   0.114  -.000558    .00006    .19631
    relative | -.000204   .000133   -1.54   0.124  -.000464   .000056    .12778
 state_pre_K | -.000835   .000387   -2.16   0.031  -.001594  -.000076     4.387
-------------+-------------------------------------------------------------
casevars     |
 p_immigrant | -.004588   .019074   -0.24   0.810  -.041972   .032796      .198
avg_pct_5_~i |  .000162   .000987    0.16   0.870  -.001773   .002097    64.946
avg_pct_fo~i | -9.6e-06   .000135   -0.07   0.943  -.000275   .000255    101.77
avg_pct_ra~i | -.000446   .000352   -1.27   0.205  -.001135   .000243    140.73
avg_pct_fe~i |  .000452   .000485    0.93   0.352  -.000499   .001403    224.03
      medinc | -.001594   .001287   -1.24   0.215  -.004116   .000928    58.109
   c_citizen | -.015822   .051365   -0.31   0.758  -.116495   .084851    .98607
     c_white |  .082073   .040908    2.01   0.045   .001894   .162252    .61483
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c_black	.058185	.040936	1.42	0.155	-.022049	.138418	.11272
c_hispanic	.09499	.04725	2.01	0.044	.002381	.187598	.17183
c_asian	-.069586	.061899	-1.12	0.261	-.190906	.051734	.041655
f_income	.017035	.009658	1.76	0.078	-.001894	.035963	2.6849
p_edu	.012989	.008788	1.48	0.139	-.004234	.030212	2.4118
f_single	.007538	.015905	0.47	0.636	-.023635	.03871	.23923
f_size	-.005006	.009736	-0.51	0.607	-.024088	.014075	4.5348
language	-.004234	.03049	-0.14	0.890	-.063995	.055526	.11061
c_siblings	-.010021	.011068	-0.91	0.365	-.031714	.011673	1.4813
f_below_po~y	-.014549	.021654	-0.67	0.502	-.056989	.027892	.21545
f_food	.017477	.014891	1.17	0.241	-.011708	.046663	1.1354
f_wic_preg~t	.014505	.020885	0.69	0.487	-.026429	.055438	.39291
f_wic_child	-.037961	.025471	-1.49	0.136	-.087883	.011961	.43428
f_food_stamp	.025236	.023705	1.06	0.287	-.021225	.071697	.05615
f_religious	-.013477	.010901	-1.24	0.216	-.034841	.007888	.57895
m_age_firs~h	-.000489	.001113	-0.44	0.660	-.00267	.001692	24.691
m_married_~h	-.0038	.01474	-0.26	0.797	-.03269	.025089	.71967
1.f_region	-.041014	.047583	-0.86	0.389	-.134275	.052246	0
2.f_locale	-.01508	.01629	-0.93	0.355	-.047009	.016848	1
c_age_prek	-.001658	.001237	-1.34	0.180	-.004083	.000767	54.471
c_female	.008183	.009512	0.86	0.390	-.010461	.026826	.48508
c_lowbirth	-.017026	.020665	-0.82	0.410	-.05753	.023477	.082043
c_preterm	.026326	.01589	1.66	0.098	-.004819	.057471	.20419
c_breastfed	.010085	.01184	0.85	0.394	-.013122	.033291	.71264
c_iep_pk	-.026638	.03124	-0.85	0.394	-.087867	.03459	.033634
c_twin	-.025617	.104085	-0.25	0.806	-.229619	.178385	.002674
c_birth_cpl	.01017	.013489	0.75	0.451	-.016268	.036608	.13932
c_first_w~15	.005488	.011523	0.48	0.634	-.017097	.028073	.22699
c_first_s~15	.000792	.019068	0.04	0.967	-.03658	.038164	.072615
4.state	-.020364	.038063	-0.54	0.593	-.094967	.054239	1

dp/dx for factor levels is the discrete change from the base level

Pr(choice = parental|1 selected) = .08430779

variable	dp/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
num							
center	-.000977	.000481	-2.03	0.042	-.001919	-.000035	9.1722
head_start	-.000136	.000099	-1.38	0.168	-.000329	.000057	1.4407
non_relative	-.000249	.000158	-1.58	0.114	-.000558	.00006	.75521
parental	.002211	.001033	2.14	0.032	.000187	.004235	.19631
relative	-.000167	.000116	-1.43	0.153	-.000395	.000062	.12778
state_pre_K	-.000682	.000365	-1.87	0.061	-.001396	.000033	4.387
casevars							
p_immigrant	.026512	.014936	1.78	0.076	-.002762	.055785	.198
avg_pct_5_~i	.000773	.000585	1.32	0.186	-.000373	.001919	64.946
avg_pct_fo~i	.000252	.000128	1.97	0.048	1.9e-06	.000502	101.77
avg_pct_ra~i	-.000233	.000174	-1.34	0.181	-.000574	.000109	140.73
avg_pct_fe~i	.000087	.000257	0.34	0.736	-.000417	.00059	224.03
medinc	-.00179	.001008	-1.77	0.076	-.003766	.000187	58.109
c_citizen	-.043707	.026846	-1.63	0.104	-.096324	.008911	.98607
c_white	-.012682	.012949	-0.98	0.327	-.038062	.012698	.61483
c_black	-.01385	.015524	-0.89	0.372	-.044276	.016576	.11272
c_hispanic	-.020273	.016408	-1.24	0.217	-.052432	.011887	.17183
c_asian	-.015062	.019181	-0.79	0.432	-.052655	.022532	.041655
f_income	-.026455	.012382	-2.14	0.033	-.050724	-.002185	2.6849
p_edu	-.028974	.013693	-2.12	0.034	-.055811	-.002137	2.4118
f_single	-.032931	.016808	-1.96	0.050	-.065875	.000012	.23923
f_size	.010057	.005879	1.71	0.087	-.001466	.021579	4.5348
language	.018789	.014142	1.33	0.184	-.00893	.046507	.11061
c_siblings	.010402	.006336	1.64	0.101	-.002017	.02282	1.4813
f_below_po~y	.002368	.008842	0.27	0.789	-.014963	.019698	.21545
f_food	-.000694	.006108	-0.11	0.910	-.012665	.011278	1.1354
f_wic_preg~t	.006396	.010503	0.61	0.543	-.014188	.026981	.39291
f_wic_child	-.016991	.013779	-1.23	0.218	-.043997	.010016	.43428
f_food_stamp	-.000466	.011117	-0.04	0.967	-.022255	.021323	.05615
f_religious	-.012882	.007808	-1.65	0.099	-.028186	.002422	.57895
m_age_firs~h	-.000691	.000698	-0.99	0.322	-.002059	.000677	24.691
m_married_~h	-.006689	.007588	-0.88	0.378	-.021561	.008183	.71967

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  1.f_region |  .017114    .04828    0.35   0.723  -.077513   .111742         0
  2.f_locale | -.006352   .008243   -0.77   0.441  -.022509   .009804         1
  c_age_prek | -.000418   .000621   -0.67   0.501  -.001635     .0008    54.471
    c_female |  .004784   .005507    0.87   0.385   -.00601   .015578    .48508
  c_lowbirth |  .002431   .010509    0.23   0.817  -.018166   .023028   .082043
   c_preterm | -.013801   .009484   -1.46   0.146  -.032389   .004787    .20419
  c_breastfed | -.013075   .008369   -1.56   0.118  -.029479   .003328    .71264
    c_iep_pk |  .011576   .017563    0.66   0.510  -.022846   .045998   .033634
      c_twin | -.014679   .053102   -0.28   0.782  -.118758   .089399   .002674
 c_birth_cpl | -.000663   .007666   -0.09   0.931  -.015688   .014362    .13932
c_first_w~15 |  .004213    .00654    0.64   0.519  -.008605   .017031    .22699
c_first_s~15 |  .010953    .01117    0.98   0.327  -.010941   .032846   .072615
     4.state | -.035436   .021614   -1.64   0.101  -.077798   .006926         1
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dp/dx for factor levels is the discrete change from the base level

Pr(choice = relative|1 selected) = .06900047
------------------------------------------------------------------------------
variable     |   dp/dx   Std. Err.    z     P>|z|  [    95% C.I.    ]       X
-------------+----------------------------------------------------------------
num          |
      center |   -.0008    .00041   -1.95   0.051  -.001603   3.2e-06    9.1722
  head_start | -.000111   .000082   -1.35   0.175  -.000272    .00005    1.4407
non_relative | -.000204   .000133   -1.54   0.124  -.000464   .000056    .75521
    parental | -.000167   .000116   -1.43   0.153  -.000395   .000062    .19631
    relative |   .00184   .000894    2.06   0.040   .000088   .003591    .12778
 state_pre_K | -.000558   .000306   -1.82   0.069  -.001158   .000042     4.387
-------------+----------------------------------------------------------------
casevars     |
 p_immigrant |   .01281   .010805    1.19   0.236  -.008366   .033987      .198
avg_pct_5_~i |  .000238   .000472    0.50   0.614  -.000687   .001164    64.946
avg_pct_fo~i |  .000114   .000077    1.48   0.138  -.000037   .000265    101.77
avg_pct_ra~i |  -.00003   .000133   -0.22   0.823   -.00029   .000231    140.73
avg_pct_fe~i |  4.4e-06   .000238    0.02   0.985  -.000462   .000471    224.03
      medinc | -.001053   .000741   -1.42   0.155  -.002505   .000398    58.109
   c_citizen |   .01443   .025431    0.57   0.570  -.035415   .064274    .98607
     c_white | -.001887   .011351   -0.17   0.868  -.024136   .020361    .61483
     c_black | -.000662   .013516   -0.05   0.961  -.027154   .025829    .11272
  c_hispanic |  .009147   .013686    0.67   0.504  -.017676    .03597    .17183
     c_asian |  .005826   .017855    0.33   0.744   -.02917   .040822   .041655
    f_income | -.000827   .003883   -0.21   0.831  -.008438   .006783    2.6849
       p_edu | -.015407   .008306   -1.85   0.064  -.031687   .000873    2.4118
    f_single |  .049158   .023982    2.05   0.040   .002154   .096162    .23923
      f_size |  .019034   .009429    2.02   0.044   .000554   .037514    4.5348
    language |  .012499    .01283    0.97   0.330  -.012648   .037646    .11061
  c_siblings | -.017765   .009072   -1.96   0.050  -.035546   .000016    1.4813
f_below_po~y | -.011812    .01019   -1.16   0.246  -.031784    .00816    .21545
      f_food |  .006386   .006647    0.96   0.337  -.006642   .019415    1.1354
f_wic_preg~t |  .016045   .012552    1.28   0.201  -.008556   .040646    .39291
 f_wic_child | -.019481   .014426   -1.35   0.177  -.047755   .008793    .43428
f_food_stamp |  .006958    .01051    0.66   0.508  -.013642   .027558    .05615
 f_religious | -.010297   .006923   -1.49   0.137  -.023866   .003272    .57895
m_age_firs~h | -.001267   .000829   -1.53   0.127  -.002892   .000358    24.691
m_married_~h |  .007498   .007687    0.98   0.329  -.007567   .022564    .71967
  1.f_region |  .046491   .044085    1.05   0.292  -.039914   .132896         0
  2.f_locale |  .012228   .010044    1.22   0.223  -.007457   .031913         1
  c_age_prek | -.000081   .000559   -0.14   0.885  -.001177   .001015    54.471
    c_female |  .005201   .005385    0.97   0.334  -.005355   .015756    .48508
  c_lowbirth |  .011977   .011157    1.07   0.283   -.00989   .033844   .082043
   c_preterm | -.008373   .007827   -1.07   0.285  -.023713   .006967    .20419
 c_breastfed | -.014722   .008863   -1.66   0.097  -.032093   .002649    .71264
    c_iep_pk | -.000451   .015401   -0.03   0.977  -.030636   .029735   .033634
      c_twin |   .00437   .049752    0.09   0.930  -.093141   .101882   .002674
 c_birth_cpl |  -.00248   .007287   -0.34   0.734  -.016763   .011803    .13932
c_first_w~15 |  .003849   .006276    0.61   0.540  -.008452    .01615    .22699
c_first_s~15 |  .011285   .010714    1.05   0.292  -.009713   .032283   .072615
     4.state |  .078338   .058926    1.33   0.184  -.037155   .193831         1
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dp/dx for factor levels is the discrete change from the base level

Pr(choice = state pre-K|1 selected) = .28239992
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variable	dp/dx	Std. Err.	z	P>|z|	[95% C.I.]		X
num							
center	-.003273	.000775	-4.22	0.000	-.004793	-.001754	9.1722
head_start	-.000455	.000266	-1.71	0.087	-.000976	.000066	1.4407
non_relative	-.000835	.000387	-2.16	0.031	-.001594	-.000076	.75521
parental	-.000682	.000365	-1.87	0.061	-.001396	.000033	.19631
relative	-.000558	.000306	-1.82	0.069	-.001158	.000042	.12778
state_pre_K	.005803	.001114	5.21	0.000	.003619	.007987	4.387
casevars							
p_immigrant	.020243	.025319	0.80	0.424	-.029381	.069868	.198
avg_pct_5_~i	-.000739	.001252	-0.59	0.555	-.003192	.001714	64.946
avg_pct_fo~i	-.000304	.000161	-1.89	0.058	-.000619	.000011	101.77
avg_pct_ra~i	.00041	.000359	1.14	0.253	-.000293	.001113	140.73
avg_pct_fe~i	-.000301	.000663	-0.45	0.650	-.0016	.000998	224.03
medinc	-.000819	.001509	-0.54	0.588	-.003776	.002139	58.109
c_citizen	.034148	.064841	0.53	0.598	-.092937	.161234	.98607
c_white	-.050834	.032754	-1.55	0.121	-.115031	.013363	.61483
c_black	.026735	.038131	0.70	0.483	-.048	.101469	.11272
c_hispanic	.008104	.03763	0.22	0.829	-.065649	.081857	.17183
c_asian	.01791	.050145	0.36	0.721	-.080372	.116191	.041655
f_income	-.032553	.012212	-2.67	0.008	-.056488	-.008619	2.6849
p_edu	-.01058	.012415	-0.85	0.394	-.034914	.013753	2.4118
f_single	-.022632	.022095	-1.02	0.306	-.065937	.020672	.23923
f_size	.012426	.011468	1.08	0.279	-.010051	.034902	4.5348
language	.049324	.032624	1.51	0.131	-.014617	.113265	.11061
c_siblings	.003484	.012507	0.28	0.781	-.021028	.027997	1.4813
f_below_po~y	.0257	.024878	1.03	0.302	-.02306	.07446	.21545
f_food	-.019093	.018191	-1.05	0.294	-.054747	.016562	1.1354
f_wic_preg~t	-.017211	.027118	-0.63	0.526	-.070363	.03594	.39291
f_wic_child	.12696	.032796	3.87	0.000	.062682	.191239	.43428
f_food_stamp	-.008068	.029558	-0.27	0.785	-.066	.049864	.05615
f_religious	.007431	.014773	0.50	0.615	-.021524	.036386	.57895
m_age_firs~h	-.003279	.001702	-1.93	0.054	-.006616	.000057	24.691
m_married_~h	-.004743	.019267	-0.25	0.806	-.042507	.03302	.71967
1.f_region	.053967	.080278	0.67	0.501	-.103375	.21131	0
2.f_locale	-.032786	.020991	-1.56	0.118	-.073928	.008356	1
c_age_prek	.004518	.001659	2.72	0.006	.001266	.00777	54.471
c_female	-.021276	.01385	-1.54	0.124	-.048421	.00587	.48508
c_lowbirth	-.013464	.027521	-0.49	0.625	-.067406	.040477	.082043
c_preterm	.008825	.018614	0.47	0.635	-.027658	.045308	.20419
c_breastfed	-.012333	.016147	-0.76	0.445	-.043981	.019315	.71264
c_iep_pk	.212373	.047103	4.51	0.000	.120051	.304694	.033634
c_twin	-.016337	.139076	-0.12	0.906	-.288921	.256247	.002674
c_birth_cpl	.024993	.019719	1.27	0.205	-.013655	.063641	.13932
c_first_w~15	.026135	.017003	1.54	0.124	-.00719	.059459	.22699
c_first_s~15	.051317	.026961	1.90	0.057	-.001526	.104159	.072615
4.state	.138673	.08533	1.63	0.104	-.028571	.305916	1

dp/dx for factor levels is the discrete change from the base level

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