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ABSTRACT

SHAPING NURTURE: EVOCATIVE EFFECTS OF CHILDREN ON THEIR ENVIRONMENTS

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Understanding how contexts shape child development is a primary goal of human development research and theory. Child effects, or the influence of children on their own environment, may be a key process by which contexts and children interact to shape subsequent development. Yet, child effects have been under-studied in social science, both theoretically and empirically.

The goal of this dissertation is to explore how children influence their own environments by evoking caregiver or parent behavior. It examines whether child language and cognitive ability shape caregiver language stimulation and the home learning environment, and whether child academic, behavioral, and health characteristics influence parental use of housing vouchers.

For the first study, I use longitudinal data from the National Institute of Child Health and Development (NICHD) Study of Early Child Care to examine whether children with more advanced cognitive and language development evoke more stimulating language environments. I find evidence for an evocative response for toddlers (15 and 24 months), but not for preschoolers (54 months). The evocative response does not vary by child care context.

For the second study, I use longitudinal data from the Children of the National Longitudinal Study of Youth to examine whether children with more advanced language

and cognitive skills evoke higher quality home learning environments, and whether these evocative effects are moderated by other child and family characteristics. Using multiple analytic techniques, I find evidence that more advanced skills do evoke higher quality home learning environments, and that these evocative effects function fairly similarly for children of different ages, gender, and socioeconomic background.

For the third study, I use data from the Moving to Opportunity (MTO) study to examine how child academic, behavioral, and health characteristics influence parental moving behavior. I find that, in particular, families with children who have multiple problems are much less likely to move than families whose children do not have problems.

By examining evocative processes across these three areas, I identify evocative processes that shape children's development contexts and discuss their implications for research, policy, and practice.

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CHAPTER ONE: INTRODUCTION

Understanding how contexts influence development is integral to the field of human development. Over the last fifty years, research has burgeoned on the impact of family, school, and neighborhood contexts, among many others, on children's development (Bronfenbrenner & Morris, 1998; Shonkoff & Phillips, 2000). These contexts are often conceptually, and nearly always methodologically, viewed as static contexts imposed upon a child (Bronfenbrenner & Morris, 1998). Although in some circumstances children have no influence on the contexts in which they develop, in many others they do. A child can influence the environment in which he develops by either actively picking or shaping contexts (active child effects) or by influencing his parents or other adults in such a way that they alter the context in which he develops (evocative child effects) (Plomin, DeFries, & Loehlin, 1977; Scarr & McCartney, 1983).

Child effects have been relatively under-studied in social science, both theoretically and empirically. Although modern theories of human development note that children can influence their own development (Bronfenbrenner & Morris, 1997), theories are often vague in the specifics of how child effects work and how important they are in shaping future developmental trajectories. Although there is a solid literature on how child behavior influences parenting (Knafo & Plomin, 2006), little is known about how child characteristics, particularly child cognitive characteristics, influence other developmental contexts such as the neighborhood, child care, school, or home learning environments.

This is unfortunate, because to the extent that child effects are important (and as noted above, little is known about how important they are outside of child temperament effects on parenting behavior), if we fail to measure or model them, this may bias our estimates of contextual effects on development.

In addition, ignoring child effects may result in inaccurate child-rearing advice and/or policy recommendations. Evocative processes may be key to understanding why some children are exposed to developmentally riskier environments than other children (Rutter, et al., 1997; Rutter, 2005). If some evocative child effects modify adult behavior such that the adult behavior negatively influences a child's developmental trajectory, we should identify such transactions and encourage caregivers and parents to be mindful of them. Knowledge and remediation of harmful evocative effects may help us improve children's long-term well-being. This dissertation aims to tackle the theoretical and empirical gaps in our understanding of evocative child effects.

Theories of child effects in historical perspective

Theories of human development place varying emphasis on the role, or lack thereof, that a child plays in shaping his own development. The blank slate, "Tabulae rasae," (Locke, 1794) perspective – "A person does not act upon the world, the world acts upon him" (Skinner, 1971, p. 211) – has remained a dominant, although not always explicitly stated, theme in much of educational, social and psychological research, and a large portion of research in these fields rarely consider the influence of the individual on the environment, in contrast to the high importance placed on the influence of the environment on the individual (Wachs, 1993).

Despite this strong environmentalist inclination – which has been particularly influential in parenting research – theoretical perspectives highlighting the role of the child or adult and his interactions with his environment have also been part of human development theory since its beginnings as a psychological science (Magnusson & Torestad, 1992). For example, James Baldwin, the father of child development research, wrote that "the individual functions and develops in a continuously ongoing, reciprocal process of interaction with his environment" (Baldwin, 1895). The intentional nature of the individual, and the dynamic relationship between the individual and his environment were also explored by Tolman (1951) in his focus on purposive behavior, as well as Lewin (1935, 1948), Murray (1938), Koffka (1935), Kantor (1924), and Kelly (1955). Following Baldwin, Jean Piaget (1954) described development as a dynamic interplay between a child and his environment, emphasizing the active role a child plays in assimilating and accommodating environmental events.

For most of the last century, however, considering the role of the child was the exception rather than the rule in most child development research. In particular, parenting research was dominated by an environmentalist perspective that rarely considered the role children themselves play in shaping parenting behavior. In 1925, John Watson's child-rearing bible influenced a generation of parents and researchers with his view, "Give me a dozen healthy infants, well-formed, and my own specified world to bring them up in and I'll guarantee to take any one at random and train him to become any type of specialist I might select" (Watson, 1925, p. 3).

In 1968, Richard Q. Bell wrote a purposely provocative conference paper (Bell, 1981) suggesting that parenting socialization researchers could have been making the wrong causal inference: child behavior might be causing parental behavior, rather than the other way around. Bell called this notion a "child effect." The same year Thomas and Chess (1968) published empirical evidence supporting a "child effects" hypothesis; they found that infant temperament influenced maternal caregiving behavior. This work fueled a plethora of empirical studies on child effects over the coming decades and solidified an explicit role for the child himself[1] in theories of human development such as interactionism (Magnusson & Allen, 1983), transactionism (Pervin, 1968), reciprocal determinism (Bandura, 1978), dialectic-contextualism (Baltes, Reese, & Lipsitt, 1980), ecological system theory (Bronfenbrenner, 1979; Bronfenbrenner & Morris, 1998), family systems theory (Whitchurch & Constantine, 1993), epigenetic theory (Gottlieb, 1991), dynamic systems theory (Thelen & Smith, 1998), and developmental contextualism (Lerner & Simi, 2000), among others. These theoretical approaches have as their goal the description of interactions among biological, behavioral, and environmental processes over developmental time and include the idea that individuals are both the products and active producers of their ontogeny and personal development over their lifespan.

The notion of genetically-driven child effects is fundamental to the behavioral genetics literature. The behavioral geneticists Plomin, DeFries, and Loehlin (1977) were the first to systematically describe passive, evocative, and active gene-environment

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[1] For space and readability considerations, I refer to the child as "he" or "himself". This choice does not intend to have gender-specific implications. All references to "he" or "himself" could also be read as "she" or "herself" if the reader so chooses.

correlations, and in 1983 Scarr and McCartney expanded this theory by suggesting that genes shape experiences and that "people make their own environments" through passive (environments provided by biologically related parents), evocative (responses elicited by individuals from others), and active (the selection of different environments by different people) genetic correlations with environments. Since the provocative Scarr and McCartney paper was published, gene-environment correlation has been well documented in child temperament and parenting in particular (Knafo & Plomin, 2006; O'Connor, et al., 1998; Moffitt, 2005; Rutter, et al., 1997), but little is known about how such processes work, or their relative influence at different developmental stages and across other predictors and outcomes, rather than just temperament and parenting.

The theoretical ideas behind child effects can be applied to other literatures as well. Resiliency research finds that disadvantaged children who are more attractive, intelligent, or sociable are more likely to receive or elicit help from teachers or other adults, which makes them more likely to succeed despite less than ideal childhood circumstances (Werner & Smith, 2001; Luthar, Cicchetti, & Becker, 2000). Although it is rarely written about as such, this process could also be modeled as an evocative process.

Economic research on the association between parental investment and children's endowments (Datar, Kilburn, & Loughran, 2005; Behrman, Pollak, & Taubman, 1995) can also be framed within the child effects perspective. For example, Becker's theories on parental investment assume an evocative effect based on the child's initial endowment. He argues that, if parents are making choices intended to maximize the aggregate welfare of their children, they might invest relatively more in children with higher marginal returns –

that is, their better endowed children (Becker & Tomes, 1976). Other theorists, however, have suggested that the evocative effect might work in the opposite direction: equity concerns might drive parents to compensate for low initial endowments by investing relatively more in their less endowed children (Behrman, Pollak, & Taubman, 1995).

Finally, child effects can be viewed from within a socio-biological/evolutionary perspective, where a child's likelihood of living until adulthood and potential for later procreation might evoke differential investment strategies by a parent (a "selfish gene" hypothesis) or a child's potential to care for the parent in old age might evoke differential investment strategies by a parent (a "selfish parent" hypothesis). This evolutionary perspective can explore how the child-parent evocative process may be a coherent behavioral, adaptive strategies designed for survival and fitness (Bouchard, 1995).

Despite the relevance of evocative effects for numerous research programs and theoretical traditions, as demonstrated above, most child effects research to date has continued to focus on child behavior and temperament effects on parenting or caregiver behavior (Kochanska, Friesenborg, Lange, & Martel, 2004; Reuter & Conger, 1998), possibly because researchers have followed the path set out on by Bell (1981, Bell & Harper, 1977), and Thomas and Chess (1968). Many studies have found an association between externalizing behavior of children and reduced quality of parenting (Simons, et al., 1994; Pianta, Sroufe, & Egeland, 1989). Some of the most compelling papers use experimental designs to identify such evocative effects of children's behavior. For example, boys with conduct disorders evoke negative, aversive behavior not only from their own mothers but also from adult strangers (Anderson, Lytton, & Romney, 1986).

Genetically-sensitive research designs have been used to identify passive (Braungart-Rieker, Rende, Plomin, DeFries, & Fulker, 1995) and evocative (O'Connor, Deater-Deckard, Fulker, Rutter, Plomin, 1998) effects of genetically-driven child behavior on parenting quality.

Overall, however, the evocative child effect process has been infrequently applied theoretically as well as infrequently tested empirically, especially on child characteristics outside of temperament and on outcomes outside of parenting behavior. The idea appears to be a useful one, however, and may be productively utilized across more disciplines than just parenting research. To do this effectively, more needs to be known about whether evocative processes are occurring as a result of child characteristics, when they are important developmentally, and whether they matter more for some children than others.

The dissertation

My dissertation explores the evocative effects of children on their developmental contexts, considering the processes, consequences, and policy implications of evocative effects. I conduct three related but distinct studies, examining the evocative effects of child cognitive and language development on child care language environments, the evocative effects of child cognitive and language development on home learning environments, and the evocative effects of child health, behavioral, and academic characteristics on parental moving behavior.

My first study examines the evocative influence of children's language and cognitive development on the language stimulation of child care providers, using the

National Institute for Child Health and Development Study of Early Child Care (NICHD-SECC). I use both OLS regression models and change models to estimate the evocative response. I also examine whether an evocative response varies by child age and child care environment and find evidence that the evocative response varies by child age, but find no evidence for it varying by child care type.

My second study examines whether a child's cognitive development and academic achievement influences the amount of stimulation received in the home learning environment. I use the Children of the National Longitudinal Study of Youth (C-NLSY) for this chapter, and use OLS, individual fixed effects, family fixed effects, and multilevel models to examine the influence of child cognitive scores on the home learning environment. I find evidence for evocative effects across all the empirical approaches, but note that the size of the effects differ depending on the empirical technique used. I find mixed evidence of moderating effects of gender, child age, family income, and parental education on evocative effects.

My third study examines whether characteristics of children influence their family's ability to successfully use a housing voucher and move to a new apartment. Using measures of children's characteristics gleaned from the baseline survey given to Moving to Opportunity participants, I find that children's academic, behavioral, and medical problems decrease the likelihood that a household will successfully move into a new apartment using a housing voucher.

Together, these studies make four primary contributions to scholarship in this area. First, the dissertation adds three studies to the limited research on child evocative effects.

Very little is known about whether parents or caregivers respond to child cognitive or achievement characteristics, and two of my studies focus specifically on this question. The other study focuses on the influence of child characteristics on parental moving patterns, a parental behavior which in turn influences children's neighborhood context.

Second, child effects have rarely been studied with large data sets and are rarely modeled across more than two waves of data due to the methodological difficulty in elucidating reciprocal pathways (Bronfenbrenner, 1979; Lynch & Cicchetti, 1998; Rutter, 2005; Crouter & Booth, 2003). Although the problem remains complex, I use multiple analytic techniques to attempt to capture the evocative effect in multi-wave studies.

Third, I am able to examine whether the evocative effect varies by child age, gender, and family socioeconomic status. For example, researchers have suggested that evocative child effects may vary by the age of the child (Reiss, 1995; Scarr & McCartney, 1983), but until now, this has not been examined. Somewhat surprisingly, I do not find much evidence for major differences in evocative effects by child age, gender, or family socioeconomic status.

Finally, I bring together perspectives pertaining to evocative child effects from across the fields of human development, developmental psychology, sociology, evolutionary theory, and economics. All of these fields have given some consideration to the issue of non-random selection into environments, and some specifically to evocative effects, but a conceptual and methodological integration across the diverse fields is sorely needed. My work in this dissertation attempts to lay the foundation for future research in the stimulating and important area of child evocative effects and development.

CHAPTER TWO: CHILD EFFECTS AND CHILD CARE:
EVOCATIVE EFFECTS OF CHILDREN'S COGNITIVE AND LANGUAGE SKILLS ON THE QUALITY OF THE CHILD CARE LANGUAGE ENVIRONMENT

Results of the most extensive and intensive investigation of the putative effects of early child care on child development to date yields several general conclusions (NICHD Early Child Care Research Network, 2003, 2006). The first is that family factors and processes appear far more influential with respect to child development—in the absence of any discounting for effects of shared genes—than does child care experience in this naturalistic, longitudinal study. Second, small to modest significant effects of child care appear to endure through the elementary school years, though they often dissipate in strength over time (Belsky, Vandell, Burchinal, Clarke-Stewart, McCartney, Owen & the NICHD Early Child Care Research Network, 2007; NICHD Early Child Care Research Network, 2005). Third, more time spent in any kind of nonmaternal care across the infant, toddler and preschool years, and particularly in center-based care, predicts higher levels of externalizing problem behavior, though time in care is not related to clinical-level behavior problems. Finally, more attentive, responsive, and stimulating care—that is, child care that is evaluated as higher in quality based upon repeated and extensive observational assessments from age 6-54 months—is associated with enhanced cognitive-linguistic functioning.

The finding that more stimulating care is associated with enhanced cognitive development has led to efforts aimed at determining why some children receive higher quality care while others do not. Researchers have found that factors related to the family's economic resources, employment, work schedules, and child care preferences, as well as the broader cultural and policy environments all play a role in influencing child care quality and type of care (Shonkoff & Phillips, 2000; NICHD ECCRN, 1996).

Child characteristics such as child age, gender, and temperament have also been shown to influence "selection" into particular types of child care (Pungello & Kurtz-Costes, 1999; Singer, Fuller, Keiley, & Wolf, 1998; Liang, Fuller, & Singer, 2000; Howes, Whitebook, & Phillips, 1992). The child characteristic most highly associated with selection into care is age; older children are more likely to be placed in care than infants (Johansen, Leibowitz, & Waite, 1996). Other child characteristics beyond basic demographics can influence selection into child care as well. For example, children exposed to risk factors at home are more likely to be placed in home-based settings or in poorer quality centers (Belsky, Spritz, & Crnic, 1996; Tresch Owen & Cox, 1988). Only one study that I am aware of has examined how child cognitive development relates to selection into child care. Using a community sample, Loeb, Fuller, Kagan, and Carrol (2005) found no influence of child cognitive competence on the type of care (e.g., family care, center care, or no care) children are placed in.

Infrequently examined in this literature, however, is the relationship between child factors and child care *quality*, particularly *child-specific* measures of process quality (Pungello & Kurtz-Costes, 1999). Child-specific process quality is measured at the individual child level, rather than just global measures of process or structural quality, and developmental theory suggests that indicators of proximal quality that influence children directly will be more important than quality factors that do not have a bearing on their immediate environment or individual experience (Bronfenbrenner & Morris, 1998; Marshall, 2004).

Analyses conducted by the NICHD Early Child Care Research Network have included only child temperamental difficulty at six months of age and child gender in their models of child care quality, but have not examined other facets of child behavior or child characteristics. The majority of other child care studies control only for child gender and age when examining child care quality in non-experimental studies, thereby making an implicit assumption that other child characteristics have no bearing on the quality of child care.

I know of only one study that has examined how child cognitive or linguistic competence influence child-care quality. Rudasill, Rimm-Kaufman, Justice, and Pence (2006) examined child temperament and language ability as a predictor of child-caregiver relationship quality in a study of prekindergarten programs. They found that measures of children's temperament and language ability at the beginning of the preschool year were associated with a measure of teacher-child relationship quality at the end of the school year. Not only did bolder children who used less complex language than other children experience more conflict with teachers, but shyer children who used more complex language were more likely to have dependent relationships with their teachers. This research suggests, then, that child factors may have an influence on a child-specific measure of teacher-child relationship quality.

Little is known about whether child care language stimulation quality (the aspect of child care quality that has the largest influence on cognitive development) may also be influenced by child characteristics, but the broader child language development literature hints that it might.

Child effects on language stimulation environments

One of the fundamental questions in child language development concerns the role of adult linguistic responsiveness in shaping children's language development. Debates over the last century have raged over the importance of exposure to adult speech in both normative language development, as well as in explaining individual differences in child language growth (Pinker, 1994). Research suggests that although adult language stimulation is not the *only* factor necessary for healthy language development, it is necessary for the development of language. Differences in the quality and frequency of mother-child interaction have also been shown to play a role in socio-economic differences in children's language development (e.g., Cross & Morris, 1980; Snow, 1989; Tamis-LeMonda, Bornstein, & Baumwell, 2001; Yoder, Warren, McCathern, & Leew, 1998; Hoff & Naigles, 2002; Huttenlocher, Haight, Bryk, Seltzer, & Lyons, 1991; Naigles & Hoff-Ginsberg, 1998). The language stimulation environment has also emerged as the key component of quality predicting children's language and cognitive development in studies of child care (NICHD, 2000).

Researchers have also found that parent-child language interaction is bi-directional. The child himself plays a crucial role in shaping language stimulation (Bohannon & Marquis, 1977), and adult language input is responsive to children's interests, communicative attempts, and language abilities (Bohannon & Bonvillian, 1997; Clarke-Stewart, VanderStoep, & Killian, 1979; Cross, 1978; Tamis-LeMonda, Bornstein, & Baumwell, 2001; Snow, 1989; Sokolov, 1993). Child characteristics such as age (Bornstein, 2000) and capacity for joint attention (Dunham and Dunham, 1992) also influence parental speech.

Less is known, however, about the extent to which children shape language stimulation provided by *non-parental* caregivers. Girolametto, Hoaken, Weitzman, and van Lieshout (2000) found that children with developmental disabilities received more directive and less frequent language stimulation from caregivers than children without disabilities. Girolametto and Weitzman (2002) reported that caregivers provided more language stimulation to groups of children who were older, and thus with more advanced language skills. The Girolametto studies, however, are small, community samples, are not able to control for all socioeconomic characteristics, only measure caregiver language stimulation at the group level, and do not compare how individual differences between children in the same age group influence language stimulation. Although the work by Girolametto and colleagues is provocative, more work needs to be done to understand the relationship between child cognitive and language characteristics and the child care language stimulation environment.

If evocative processes do influence language stimulation received in child care, it raises the question of whether the positive associations between the linguistic richness of childrearing environments and children's cognitive-linguistic skills are, at least in part, the result of evocative child effects. Children with more advanced language or cognitive skills may simply evoke greater amounts of speech and/or higher quality speech from their parents and caregivers.

For example, the Rudasill, Rimm-Kaufman, Justice, and Pence (2006) findings are notable because the teacher-child relationship "outcome" used in their investigation has been treated as an exogenous indicator of child care quality in research attempting to model the effects of good quality care on children's later development (Peisner-Feinberg, et al., 2001). Their results suggest that there is child temperament-related endogeneity in measures of child-specific, child-teacher relationship quality, and raises the question as to whether there might be child cognitive- or language-related endogeneity in measures of child-specific child care language stimulation quality.

To the extent that this is the case, evocative child effects could masquerade in both cross-sectional and longitudinal correlational research as effects of language stimulation on children's language development. Not controlling for such effects in non-experimental studies may bias estimates of contextual factors on development (Singer, Fuller, Keiley, & Wolf, 1998).

Evocative effects are of a concern not just for endogeneity reasons, but also for practice- and policy-relevant reasons. If caregivers are providing greater language stimulation to children with already more advanced language skills, this may have implications for the ongoing language and cognitive development of children with less advanced skills (Bohannon & Bonvillian, 1997). Language input plays a role in driving future language growth, so it may be important for caregivers of children at risk for poor language or cognitive skills to attempt to counteract any “natural” propensity to talk less to them.

Unfortunately, not enough is known about evocative child effects, particularly within the child care setting and with respect to child cognitive and language development. This is surprising, as developmental theory suggests that specific child-caregiver interactions – which evocative child effects are – might be key transactional processes by which child care quality influences children’s development (Marshall, 2004).

The current study

In the current study, I address the following question: Do children’s cognitive, language, or developmental skills influence the language stimulation they experience in child care? Based on the research suggesting caregiver and parental tuning to child developmental level, I predict that more developmentally advanced children, in terms of their performance on standard developmental assessments, will evoke and thus receive more language stimulation from their caregivers than will less competent agemates.

Analytic approach

I use a longitudinal design to estimate effects of child characteristics on the quality of care at multiple points in time across early childhood. I test for child effects by using a measure of the child (e.g., developmental status in Study 1) at one point in time (e.g., 15 months) to predict child care experience at concurrent and subsequent measurement occasions.

In order to measure evocative effects of children on their environment, one must employ an analytic strategy that can separate out the effect of the environment on the child from the effect of the child on the environment. Although the best way to do this is using an experimental or quasi-experimental design, using a longitudinal approach is preferred to cross-sectional analyses (Rutter, Pickles, Murray, & Eaves, 2001). For example, Roberts & Robins (2004) used a longitudinal design to determine the effect of work experiences on personality development as well as the effect of personality traits on selection into different work experiences. Miech, Caspi, Moffitt, Wright & Silva (1999) also used a longitudinal design to examine the extent to which socioeconomic status is a cause or a consequence of mental illness. Similarly, I use three different types of longitudinal models to test for the effect of child language and cognitive skills on the caregiving language environment.

With equation 2.1, I estimate the size of the evocative effect of early measures child cognitive and language characteristics (at 15, 24, and 36 months) on later measures of language stimulation environments (24 months, 36 months, and 54 months). By using a prior measure of cognitive development, I can ensure that it is not influenced by the child's current level of language stimulation. Using a lagged measure of the time-variant predictor of interest has been advocated by methodologists as one way of addressing the problem of reverse causation, although it is not without its drawbacks, as I discuss below.

$$\textbf{(2.1)}\ \mathbf{LNGSTIM_{ti} = \beta_0 + \beta_1 COG_{(t-1)i} + \beta_2 CHILD_i + \beta_3 FAM_i + \beta_4 FAM_{ti} + \beta_5 CARE_{ti} + e_i}$$

In equation 2.1, I include a large battery of child time-invariant ($CHILD_i$, which includes gender, race, and temperament at six months), family time-invariant (FAM_i, which includes one-time measures of maternal education, verbal ability, maternal sensitivity and depression), family time variant characteristics (FAM_{ti}, which includes family income-to-needs ratio, home environment, and father presence assessed at each time point) and time-variant child care characteristics ($CARE_{ti}$, which includes type of care, caregiver education, child-caregiver ratio, and amount of time spent in child care assessed at each time point).

There are drawbacks to equation 2.1. Note that this model assumes that a child's current level of language stimulation provided by a caregiver is a function of the child's *past* cognitive ability. Although using the prior measure of cognitive ability ensures that it is not being influenced by the current measure of language stimulation, coefficients are likely to downwardly biased due to the mis-timing of the evocative effect .

In addition, to the extent that there are omitted variables correlated with both the child's cognitive score as well as the child's language stimulation variable, this biases the OLS estimates in equation 2.1. As the child is not related to his caregiver, genetic confounds are unlikely to be a problem here. However, if parent and child care covariates are unable to capture parental selection into particular types of child care, this could bias estimates. For example, parents with higher language ability may have children with higher language ability and also choose child care centers which have "better" language stimulation environments.

It seems likely that caregivers respond to children's language and cognitive development on a shorter time horizon, so I also examined the contemporaneous evocative effect of child language or cognitive skill on language stimulation (Equation 2.2). This model is arguably is a better fit for the timing of the evocative process, as one would expect a caregiver to respond to a child's current developmental competence rather than a child's prior developmental competence.

$$\textbf{(2.2) } \mathbf{LNGSTIM_{ti} = \beta_0 + \beta_1 COG_{(t)i} + \beta_2 CHILD_i + \beta_3 FAM_i + \beta_4 FAM_{ti} + \beta_5 CARE_{ti} + e_i}$$

To further limit the possibility that children with particular individual or family characteristics are selected into language stimulation environments of varying quality, I include the same child, household, and child care time-variant and time invariant covariates from equation 2.1.

For those time points in which I have a prior measure of language stimulation, I also run a model that includes a measure of prior language stimulation, which limits the potential influence of unmeasured confounding variables:

$$\textbf{(2.3) } \mathbf{LNGSTIM_{ti} = \beta_0 + \beta_1 LNGSTIM_{t\text{-}1i} + \beta_2 COG_{(t)i} + \beta_3 CHILD_i + \beta_4 FAM_i + \beta_5 FAM_{ti} + \beta_6 CARE_{ti} + e_i}$$

In equation 2.3, child language stimulation environment at Time 2 for child i is expressed as a function of child developmental characteristics at Time 2, controlling for a Time 1 measure of the outcome. Including the Time 1 language stimulation outcome controls for time-invariant differences between children's language stimulation environments (both measurable and not) that were present at the first wave of data collection. To further limit the possibility that children with particular individual or family characteristics are selected into language stimulation environments of varying quality, I include the same child, household, and child care time-variant and time invariant covariates from equation 2.1.

This approach makes the assumption that unobserved, confounding variables have similar impacts on both early and later outcomes and that the error in assessment at both ages is random. To the extent that the impact of child, family, or child care characteristics on child cognitive/language development and the language stimulation environment differ between the two points in time, this may bias estimates. My results should be interpreted in light of this limitation.

Finally, I use a change model method to examine how changes in child cognitive scores are related to changes in the language stimulation environment. It begins with a model (equation 2.4) that assumes language stimulation is related to the child's current cognitive or language facility, as well as other time-variant and time-invariant child and family characteristics. Following this, equation 2.5 models prior levels of language stimulation.

$$(2.4)\ \mathbf{LNGSTIM_{ti} = \beta_0 + \beta_1 COG_{(t)i} + \beta_2 CHILD_{(t)i} + \beta_3 FAM_{(t)i} + \beta_4 CARE_{(t)i} + \beta_5 CHILD_i + \beta_6 FAM_i + e_i}$$

$$(2.5)\ \mathbf{LNGSTIM_{t-1i} = \beta_0 + \beta_1 COG_{(t-1)i} + \beta_2 CHILD_{(t-1)i} + \beta_3 FAM_{(t-1)i} + \beta\, CARE_{(t-1)i} + \beta_5 CHILD_i + \beta_6 FAM_i + e_i}$$

The change model is generated by subtracting equation 2.5 from equation 2.4.

$$\textbf{(2.6)}\ \Delta LNGSTIM_{(t,\ t\text{-}1)i} = \beta_0 + \Delta\beta_1 COG_{(t,\ t\text{-}1)i} + \Delta CHILD_{(t,\ t\text{-}1)i} + \Delta FAM_{(t,\ t\text{-}1)i} + \Delta CARE_{(t,\ t\text{-}1)i} + e_i$$

In equation 2.6, the time invariant terms in equations 2.4 and 2.5 cancel each other out and change in language stimulation between two points in time is modeled as the effect of change in children's cognitive scores between two points in time, as well as changes in other time variant characteristics. The advantage of using this model is that biases associated with unmeasured and measured, time-invariant characteristics are eliminated. One drawback for this model due to the data in the present study is that the cognitive measures differ across each time point (Bayley Version 1 at 15 months, Bayley Version 2 at 24 months, an average of two different Reynell measures of language ability at 36 months, and Woodcock Johnson at 54 months), so the "change" in cognitive measure represents a "change" in the child's standardized cognitive score across different measurements, which will likely increase the size of the standard error.

Method

Data for this study come from the NICHD SECC, which recruited mothers from hospitals near the following locations throughout 1991: Little Rock, Arkansas; Irvine, California; Lawrence, Kansas; Boston, Massachusetts; Philadelphia, Pennsylvania; Pittsburgh, Pennsylvania; Charlottesville, Virginia; Morganton, North Carolina; Seattle, Washington; and Madison, Wisconsin. The sample plan was not intended to provide a representative national sample but to represent healthy births to nonteen parents at the selected hospitals. Potential participants were selected from among 8,986 mothers giving birth during selected 24-hour sampling periods. The sample of 8,986 mothers was reduced to 5,416 mothers eligible for a phone call two weeks after the birth owing to both unplanned attrition (438 cases; mostly refusals) and planned sample exclusions (3,142 cases; mother under 18 years old, multiple births, mother not fluent in English, family expects to move, medical complications, baby being put up for adoption, family lives too far away, family participates in another study, family lives in an unsafe neighborhood). A conditional subsampling plan was next imposed to ensure that single-parent, low-maternal education, and minority distributional targets were met while continuing random selection of cases. Altogether, 3,015 families were targeted for recruitment (NICHD Early Child Care Research Network, 1994).

The sample was further reduced from 3,015 screened mothers to the 1,364 recruited mothers who provided information at the 1-month interview for reasons that were unplanned (1,153 cases; refusals and lack of success with contacts at three different times of the day) and planned (151 cases; baby in hospital more than seven days, planning to move within three years, 185 cases not contacted because enrollment quota was achieved before that family's name appeared on the contact sheets). Thus, because of attrition and the inclusion of the 10 sites selected nonrandomly, the NICHD SECC sample cannot be regarded as statistically representative of any a priori-defined population. Nevertheless, the sample is large and economically, geographically, and ethnically diverse, especially for an observational child care study (NICHD Early Child Care Research Network, 1994).

The analytic sample for the current study is comprised of 1,140 children, 748 of whom were in nonparental child care at 24 months, 832 of whom were in such child care at

36 months, and 914 of whom were in such child care at 54 months. Nearly half, or 536 children, were in nonparental care at all three waves. Excluded from analysis were 224 children who were cared exclusively by parents at 24, 36 and 54 months of age. These excluded children—who lacked any measurement of language stimulation experienced in child care—were from less privileged families (i.e., lower income, less maternal education, younger mothers).

Procedures and Measurement

Procedures and measures are described in terms of the roles that they play in the statistical analysis: outcome to be predicted (i.e., caregiver language stimulation), primary predictors of interest (i.e., child cognitive-linguistic skill) and control variables (i.e., family background factors and child care variables).

Outcome measure: Child caregiver language stimulation.

Observational assessments of caregiver-child interaction were obtained for children who were in 10 or more hours per week of nonmaternal care. Observations were conducted during two half-day visits scheduled within two-week intervals at ages 6, 15, 24, 36 months and during one half-day visit at 54 months. At each visit, observers completed two 44-minute cycles of the Observational Record of the Caregiving Environment (ORCE), during which they first coded the frequency of specific caregiver behaviors and then rated the quality of the caregiving.

Target children were observed in their child care arrangement with the most hours. Usually two "cycles" of observations were made on each of two different days, for a total of four "cycles." Each cycle consisted of thirty 30-second segments of observation alternating with 30 seconds of recording time. All behavioral items were then summed across segments and cycles to yield a total number of segments within which a particular behavior (or set of behaviors) occurred. Most children had a total of 120 segments of information. The individual behavioral variables (e.g., showed positive affect, positive physical contact, responds to child's vocalizations) were scaled to represent the number of times in 60 segments a particular behavior occurred. Composite variables (e.g, language stimulation, physical care, negative interaction) were created as the sum of the standardized individual behavior variables. Final values for the individual and composite behavioral variables were retained only for those children with a minimum of 45 segments. The internal consistency of these composites was high, with Cronbach's alphas of .88, .92, .90, and .66 at 15, 24, 36, and 54 months, respectively. The 54-month reliability was lower due to only two observation cycles being conducted, compared to four cycles at the earlier points in time.

The caregiver behaviors that were categorized as language stimulation varied somewhat by child age. At 15 months, they were: asks questions of child, responds to child's vocalizations, and other talk to child (mean=0, SD=1; only the standardized composite variable was available). At 24 and 36 months, they were: asks questions of child, responds to child's talk, and other talk to child (24 months mean=50.6, SD=27.1; 36 months mean=58.4, SD=30.7). At 54 months, they were: asks questions of child, answers child's question, and other talk to child (mean = 36.6; SD=17.9). Distributions of the outcome variables were normal.

Each ORCE observer was trained to reach criterion using videotapes that had been coded by experts. The criterion was 60% straight match with the expert coder. The criterion was 80% agreement with the expert for grouped codes (for details see NICHD Early Child Care Research Network, 1996). Live inter-observer reliability was also calculated three to four times at approximately 3-month intervals throughout each data collection period. Intraclass correlations among partners ranged from .89 to .99 (Winer, 1971).

Primary predictors of interest: Child cognitive/language skills.

The Mental Development Scale (MDI) of the Bayley Scales of Infant Development (BSID) were used to measure children's cognitive development. At 15 months, the first version of the MDI (Bayley, 1969) was used and at 24 months, the second version of the MDI (Bayley, 1993) was used. The BSID is an individually administered examination designed to assess the current developmental functioning of infants and children ages 1-42 months. The MDI section of the BSID is a 30-minute assessment of infants' sensory-perceptual, memory, and problem-solving abilities (e.g. block building, puzzles, and vocabulary) that provides a general measure of cognitive development. Bayley scores were expected to provide an index of the infant's complex maturational system (attentional, self-regulatory, and verbal abilities). Administration of the Mental Scales for each test yields a raw score which represents the total number of items passed. The raw score is converted into the Mental Development Index (MDI) score by referring to the norms tables for the child's age derived by Bayley (1969; 1993). The original Bayley, and subsequently, the revised Bayley, are the most widely used measures of infant cognitive ability and have been shown to have excellent psychometric properties (Gagnon & Nagle, 2000).

The child cognitive measures at 36 months reflected expressive language and vocabulary comprehension, measured with the Reynell Scales of Language Development (Reynell, 1991). The Verbal Comprehension Scale at 36 months consists of ten sections, for a total of 67 questions, which follow the developmental sequence of receptive language skills. The child as required to follow the examiner's directions pertaining to models of familiar objects (i.e., doll, car, spoons, etc.) and representations of objects, people and animals. Questions are arranged in order of increasing difficulty where the directions become more abstract (e.g., "Who used to go to school but doesn't now?) and more complex (e.g., "Put all the pink pigs round the outside of the field."). The Expressive Language Scale assesses expressive language skills, using three sets of items: structure (from vocalizations to the appropriate use of syntactic structure), vocabulary (naming of objects, actions, and concepts), and content (the use of language to describe elements and actions). Reliability for the Reynell is high, with the test developer reporting median split-half reliability coefficients of .87 for both sections (Reynell & Gruber, 1990).

At 54 months a measure of child's linguistic-cognitive competence was created by compositing four standardized scores based on select language-related subtests of the Woodcock-Johnson achievement battery (Woodcock & Johnson, 1990): the Picture Vocabulary, Incomplete Words, Memory for Sentences, and Letter Word tests (alpha=.74). The Picture Vocabulary subtest measures the child's ability to recognize or to name pictured objects. Six of the beginning items are in a multiple-choice format that requires only a pointing response from the subject. The remaining items require the subject to name familiar and unfamiliar pictured objects. In the Incomplete Words subtest, after hearing a recorded word that has one or more phonemes missing, the subject names the complete word. The Memory for Sentences subtest measures the ability to remember and repeat simple words, phrases, and sentences. The Letter-Word Identification subtest includes five items that tap the ability to match a pictographic representation of a word with an actual picture of the object. The remaining items measure the subject's reading identification skills in identifying isolated letters and words.

At each wave, all measures of child competence used to predict language stimulation were standardized to have a mean of zero and a standard deviation of one.

Control variables: Child/family background factors.

The demographic controls included child gender, child ethnic group (non-Hispanic African American, non-Hispanic European American, Hispanic American, or other), maternal years of education at child's birth, average family income-to-needs ratio from six months up to the outcome measure month, and the percentage of measurement occasions when a partner lived in the household. Each of these has been related to child care experiences (Pungello & Kurtz-Costes, 1999).

Child difficult temperament at 6 months was measured by a 55-item Infant Temperament Questionnaire (Medoff-Cooper, Carey, & McDevitt, 1993) completed by the child's mother. Using a 6-point scale, mothers rated how frequently their children's behavior was similar to example behaviors (e.g., "My baby's initial reaction to a new babysitter is rejection (crying, clinging to the mother, etc.)."). An overall measure of difficulty was obtained by averaging nonmissing items from the Activity, Adaptability, Approach, Mood, and Intensity subscales. Cronbach's α for the entire NICHD SECCYD sample was .81. The dimensions of activity, approach, adaptability, mood and intensity were selected to provide maximum information about the infant's temperament with minimum administration time.

When the child was six months, maternal sensitivity (positive, nonintrusive, responsive, and supportive maternal care) was coded from videotaped 15-minute mother-child observations during semistructured play at six months. The maternal sensitivity score was a composite of 4-point ratings of sensitivity to nondistress, intrusiveness (reverse scored), and positive regard. Videotapes from all sites were coded at one location (see NICHD Early Child Care Research Network, 1999b, for details). At the 6-month assessment, each mother was instructed to play with her infant using several toys for a 10-min period. All observations were recorded on videotape, which were then sent to a central site for coding. Coders were blind to the infants' child care status. A composite variable was created by summing the mother's scores on the individual coding scales for sensitivity to nondistress, positive regard, and intrusiveness (reverse scored). Intercoder reliability was .87 and .83 for the 6 and 15 months composites, respectively, while Cronbach's alpha was .75 and .70 for the 6- and 15-month composites, respectively. These two scores were averaged to create an overall maternal sensitivity composite score used in the analyses in this report.

Maternal depressive symptoms were measured using the Center for Epidemiological Studies Depression Scale (CES –D, Radloff, 1977) administered at six months. Maternal vocabulary was assessed by the Peabody Picture Vocabulary Test – Revised (PPVT–R; Dunn & Dunn, 1981), which was administered to mothers when their children were 36 months old. Each of these family characteristics was included because they had been linked theoretically or empirically to both child outcomes and family selection of child care arrangements (Pungello & Kurtz-Costes, 1999).

Quality of home environment was measured with the Infant/Toddler version of the Home Observation for Measurement of the Environment (HOME; Caldwell & Bradley, 1984), which is an assessment of the overall quality of the physical and social resources available to the child in the family context. Different measures of the HOME were used at different times. The Infant/Toddler version was administered at 6 and 15 months, and the Early Childhood version was administered at 36 months. Both versions measure the quality and the quantity of stimulation and support available to a child in the home environment. Analyses used the total HOME. There was no 24-month HOME observation, so I used the average of the 6- and 15-month scores for estimating caregiver home environment at 24 months. Cronbach's alpha was .77 for the 6 months score, .80 for the 15 months score, .87 for the 36 months score, and .72 for the 54 months score.

A more targeted measure of maternal cognitive stimulation was obtained from a semi-structured mother-child interaction procedure conducted and videotaped at the family's home at six months. At six months, mothers were instructed to play with their children using toys in two containers. Some of the toys were provided by the experimenter, and others were the child's toys that were selected by the mother. All tapes were coded at a central location by coders who were unacquainted with the family or child care history.

Maternal stimulation of cognitive development was rated for the number and quality of activities presumed to enhance perceptual, cognitive, linguistic, and physical development on a 4-point scale at six months. Low scores indicate that mothers made little or no attempt to stimulate or teach the child, were totally uninvolved, or provided stimulation that was very poorly matched to the child's developmental level or interest. High scores indicate that mothers consistently provided age-appropriate cognitive stimulation that was likely to lead to a higher level of mastery, understanding, or sophistication. Inter-coder reliability in coding maternal stimulation during mother-child play, calculated using intraclass correlations (Winer, 1971) was .81 at six months.

Control variables: Child care type and quality.

Features of child care were assessed at each measurement occasion; these included study site, observed child-caregiver ratio, years of caregiver education, mean hours of care per week, and an indicator variable for whether the child was in home care (with being in center care the comparison group).

Missing data

Missing data is a concern in most longitudinal data sets, and the rate of missing data in the NICHD SECC is as much as 25 percent (25 percent had missing items on at least one variable) for reasons including caregiver refusal, child absence from child care, and recent changes in the child care setting (see NICHD Early Child Care Research Network, 1996). Families with fewer missing values had higher incomes and provided more stimulating home environments; the mothers had more education, higher PPVT scores, and were rated as more stimulating in interactions with the child; and the observed children experienced more hours of child care and were more likely to be in a child care center or a child care home than to be in less formal child care. The high rate of missing data and non-random nature of missingness mean that many common strategies for dealing with missing data, such as listwise deletion, mean substitution, and indicator or dummy variable adjustment, may generate biased estimates and/or distort statistical power (Little & Rubin, 2002; Acock, 2005; Schafer & Graham, 2003). Over the last few decades, statisticians and social scientists have increasingly called for using other methods, such as multiple imputation, to deal with missing data, rather than the more traditional methods.

In multiple imputation, each missing value is replaced by two or more imputed values representing a distribution of possibilities for that value, with estimates based on non-missing values. The idea behind multiple imputation is that if several different complete datasets (rather than just one) are obtained by imputing missing values, then the researcher can take into account the uncertainty involved in imputing missing values by examining the variation between inferences obtained in each of the completed datasets; final estimates and standard errors are thus adjusted for the uncertainty due to missing data.

The key assumption when employing multiple imputation is that the missing data are missing at random (MAR). The missing data for a variable are MAR if the likelihood of missing data on the variable is not related to the participant's score on the variable, after controlling for other variables in the study. For the two studies presented here, this means that the missing data imputation algorithm should include all possible variables that correlate with missingness, such as poverty, education level, and child care type. Unfortunately, the MAR assumption cannot be formally tested except by obtaining follow-up data from nonrespondents (Graham & Schafer, 2001), which was not done in this study. However, due to the inclusion of a large number of covariates in our missing data imputation, I believe that applying the MAR assumption is not entirely unreasonable. Graham & Schafer (2001) also suggest that minor violations of MAR typically have negligible effects on estimates and standard errors.

The STATA program "ice" was used to impute missing values by using switching regression, an iterative multivariable regression technique (Royston, 2004, 2005). All variables being used in the subsequent analysis were used to impute missing values. The iteration was run ten times, which is generally considered an efficient number of iterations to generate precise estimates (Schaffer & Graham, 2002). The ten sets of imputed and nonimputed variables were stored to a new file and this was used for the regression analyses. Another STATA command, "micombine," combines across the replicates to estimate the regression model. Analyses were also run with the non-imputed dataset (using missing data dummies) and the overall pattern of results were similar. The language stimulation outcome variables were not imputed.

Results

Do children's language and cognitive skills predict future language stimulation provided by caregivers in child care?

As a first step in addressing this question, bivariate associations linking children's cognitive-linguistic functioning and language stimulation were examined, both within and across time. Table 2.2 shows that child language and cognitive measures at 15, 24, 36, and

54 months were positively and significantly correlated with language stimulation measures at 15, 24, and 36 months. As stated earlier, these associations could be the result of three processes: the effect of caregiver language stimulation on child scores, the effect of child scores on caregiver language stimulation, and/or the effect of “third variables” on both child scores and caregiver language stimulation.

To further illuminate potential evocative effects of child cognitive-linguistic skill on language stimulation, I examined associations between a child’s language or development score and later language stimulation (equation 2.1, as detailed in the analytic approach). In Table 2.3, I present results from regressions of evocative effects of children’s language or cognitive development on the language stimulation experienced in child care at three different ages: 24 months, 36 months and 54 months. For each time point, two regressions were performed, one without controls and one with all controls detailed in equation 2.1.

24 months. A 1 SD higher 15-month Bayley score predicts .13 SD ($p < .01$) more caregiver language stimulation at 24 months, with no controls (Model 1). When the battery of controls is included (Model 2), the coefficient decreases to .10 SD ($p < .01$).

36 months. A 1 SD higher 24-month Bayley score predicts .10 SD ($p < .01$) more caregiver language stimulation at 36 months, with no controls (Model 1). When the battery of controls is included (Model 2), the coefficient declines to .07 SD and is no longer significant.

54 months. A 1 SD higher Reynell comprehension scale at 36 months is associated, somewhat surprisingly, with .11 SD ($p < .01$) *less* language stimulation at 54 months, whereas a 1 SD higher Reynell expressive scale at 36 months is associated with a .10 SD ($p < .01$) *more* language stimulation at 54 months, with no controls (Model 1). These coefficients reflective of child effects *increase* in magnitude when controls are added to the model (Model 2), with a 1 SD higher score on the Reynell comprehension scale at 36 months being associated with.15 SD ($p < .01$) *less* language stimulation at 54 months; and a 1 SD higher score on the Reynell expressive scale at 36 months being associated with .12 SD ($p < .01$) *more* caregiver language stimulation at 54 months. The fact that the coefficients increase in size with the inclusion of family controls suggests that family selection serves to suppress evocative child effects.

This same reversed pattern of comprehension-expression prediction emerged when the 54-month language-stimulation composite was decomposed into its three constituent elements—frequency of being asked questions, caregiver responses to child vocalizations and other (non-negative) talk—and (unreported) analyses were rerun using these three variables as language stimulation outcomes to be explained (results not shown).

I ran a full model (not shown), with age interactions, to examine whether the coefficients on the various cognitive-language scores at 15, 24, and 36 months are different from one another at standard levels of statistical significance. The coefficient on the Reynell vocabulary comprehension score was statistically significant at ($p < .05$) from all the other coefficients, but the rest of the coefficients were not statistically significantly different from one another.

Do children's language and cognitive skills predict contemporaneous language stimulation provided by caregivers in child care?

In Table 2.4, I present results from regressions of evocative effects of children's contemporaneous language or cognitive development on the language stimulation experienced in child care at three different ages: 24 months, 36 months and 54 months. First, I regressed language stimulation at time *t* on child's language score at time *t* with a battery of controls (equation 2.2). Then, I included a lagged measure of language stimulation, as is detailed in equation 2.3.

15 months. Children scoring 1 SD higher Bayley at 15 month old score receive .12 SD ($p < .01$) more language stimulation at 15 months (Model 1). I cannot control for prior language stimulation with this model because there was no measure of language stimulation prior to 15 months.

24 months. Children scoring 1 SD higher on the Bayley 24 month old receive .24 SD ($p < .01$) more language stimulation at 24 months. When a measure of prior language stimulation is included in the model, the coefficient drops to .15 SD ($p < .01$).

36 and 54 months. Child language scores at 36 months were *not* associated with language stimulation at 36 months, nor was the 54 month WJ score associated with 54 month language stimulation.

I ran a full model, with age interactions, to examine whether the coefficients are different from one another. The 15 month and 24 month coefficients were not different from one another at standard levels of statistical significance ($p < .05$). Both, however, were different at significant levels from the 36 and 54 month coefficients.

Do changes in children's language and cognitive skills predict changes in language stimulation provided by caregivers in child care?

In Table 2.5, I present my results from the change model (equation 2.6). A 1 SD change in children's standardized Bayley scores between 15 and 24 months is associated with a .08 SD ($p < .05$) increase in language stimulation between 15 and 24 months. I do not find statistically significant effects of change in cognitive scores on change in language scores for the other time points.

Non-linear models.

I examined whether there might be a non-linear relationship between child cognitive or language scores and the language stimulation environment. When I ran models with an exponential variable included, as well as models with dummy indicators, these models did not add any explanatory value or allow for a better fit for the data. Results are available by request.

Sub-group effects.

I examined whether evocative effects might be larger in different child care settings, different size child care groups, or with caregivers with different education levels. I examined this by running models with interactions between an indicator variable (center care vs. home care; high vs. low child-caregiver ratio; high vs. low caregiver education) and all other variables in the model. The size of evocative effects did not vary across these subgroups. Results are available by request.

Findings from the full models.

Although this study's focus is on the evocative effects of child language/cognitive developmental competence, it is useful to note how other child, family, and child care factors influence language stimulation in child care. Full model results the contemporaneous model, with lagged dependent variable (equation 2.3) are discussed next (Table 2.6).

15 months. At 15 months, there were no other "child effects" other than a child's developmental competence: gender, race, temperament, and age did not affect language stimulation. An additional year of maternal education is associated with .04 SD less language stimulation in child care. However, family and site factors did influence the quality of language stimulation in child care. Both a higher income-to-needs ratio (higher income families) and better home environment scores predict better child care quality. There is also a strong positive site effect from "site 3" (New Hampshire) compared to the reference site (Arkansas). Moving from 1 children per caregiver to 2 child per caregiver is associated with .28 SD less language stimulation, while an additional hour is associated with .01 SD less language stimulation. Being in a "home day care" rather than center based care (the reference group) is associated with .40 SD more language stimulation. Having more children per caregiver and more hours in care are associated with less language stimulation.

24 months. At 24 months, there is an effect of race on the language stimulation environment. Black children received .32 SD less language stimulation than white children (the reference group) before controlling for their Bayley score and .29 SD ($p < .10$) less after controlling for it. A higher income to needs ratio was associated with more language stimulation. Site effects operated, with site 1 (California) having lower language stimulation than the reference site (Arkansas). Having more children per caregiver were associated with less language stimulation.

36 months. Interestingly, only the child-caregiver ratio had an independent influence on the quality of the language stimulation environment at 36 months.

54 months. At 54 months, black children received .42 SD lower language stimulation than white children, after controlling for other factors. There were also a few site factors, with sites 6 and 8 (Virginia and West Carolina) receiving less language stimulation than the reference group (Little Rock). Having more children per caregiver were associated with less language stimulation, and caregivers with more education provided more language stimulation. Children in home care also received more language stimulation.

Discussion

In light of extensive correlational evidence highlighting “effects” of the richness of the family language environment on children’s cognitive-linguistic development (e.g., Hart & Risley, 1995) and related and extensive evidence documenting “effects” of child care quality on children’s cognitive-linguistic functioning (e.g., NICHD Early Child Care Research Network, 2000, 2005, 2006), and especially the potential influence of language stimulation (NICHD Early Child Care Research Network, 2000), the research reported herein was designed to examine a reciprocal process of influence, namely, the potential “effect” of children’s developmental status (at 15 & 24 months) and cognitive-linguistic skill (at 36 months) on the language stimulation experienced in child care during the infant, toddler and preschool years. This work was motivated by research and theory highlighting child effects on parenting and thus the possibility that such child effects may operate in child care settings as well. By taking advantage of perhaps the most extensive database available pertaining to children's experience in child care, I examined the existence and magnitude of child effects on language stimulation experienced in child care.

Evidence for evocative effects

Results of this longitudinal, but non-experimental, inquiry suggest that young children's cognitive-linguistic development may influence the quality of care they receive in child care, with quality defined for purposes of this inquiry in terms of language stimulation. Results suggest that these evocative effects may vary by child age, as well as by what child competencies appear responsible for them.

It seems notable that the detected evocative effects of developmental competence were different across children's ages. This suggests that there may be differences in how susceptible caregivers are to variation in children's developmental capabilities depending on how old children are. Models controlled for a host of family and child care variables, so any changes in family or child care characteristics that might also produce this effect would seem to be diminished.

Intriguingly, it was not only the magnitude of detected child effects that changed over time, but the very nature of the effects themselves. Whereas the evocative effects of 15-month developmental status (i.e., Bayley) with both 15-month and 24-month language stimulation, 24-month developmental status with 24-month language stimulation, and 36-month expressive language with 54-month language stimulation, as well as the change model between 15 and 24 months were positive and consistent with the squeaky-wheel hypothesis, suggesting that more developmentally and linguistically skilled children evoke greater language stimulation from caregivers, recall that the child effect pertaining to 36-

month language comprehension with 54-month language stimulation was negative: The more words and phrases children understood at age three, the *less* language stimulation they experienced in child care when 54 months of age. Yet, child language scores at 36 months had no influence on language stimulation at 36 months. More work is necessary to discern why such effects would vary depending on the predictor used.

Given the unexpected nature of these findings, any attempt at explanation must be regarded as speculative. The effects may be due to the nature of the child's language environment changing between 3 and 4 ½ years of age. By 4 ½ years of age, children are in pre-kindergarten, and conceivably, language stimulation is truly evoked from caregivers by children who are highly skilled in verbally *expressing* themselves, if only because such children are difficult to ignore. Yet when children are highly skilled in *understanding* what is said to them, perhaps caregivers have less need to repeat themselves and thereby end up speaking less with children who comprehend spoken language better than agemates. Perhaps this is due to the fact that caregivers, in attempt to get themselves understood by the latter, repeat themselves more than would otherwise be the case, thereby leading to high levels of language stimulation in the case of children with limited comprehension. Another possibility is that training for preschool-aged teachers in how to verbally interact with preschool aged children is different than training for caregivers of toddlers. Unfortunately the measures of language stimulation are unable to identify the content or nature of caregiver language. More work is clearly needed to unpack these surprising results.

The change model is arguably the strongest model, as it significantly reduces the likelihood that estimates are biased upward by unmeasured time-invariant characteristics of the child or family. At the same time, change models invariably introduce more measurement error. As the measures of child cognitive and language skill vary across all four points in time, and I can only compare standardized measures, this is an especially pertinent issue. Despite these drawbacks, the change model between 15 and 24 months did reveal evocative effects: a 1 SD increase in child cognitive skill between 15 and 24 months was associated with a .08 SD increase in language stimulation between 15 and 24 months. This is slightly smaller than the coefficients associated with the prior and contemporaneous models, but not a sizeable difference. Overall, evocative effects at 15 and 24 months held up best across the three types of models.

Results from the full models are also intriguing and suggest that child race may be a significant influence on language stimulation quality, even after controlling for a large battery of child, family, and child care characteristics. Black children received lower quality language stimulation quality overall, but even after a full set of covariates are accounted for, black children still receive less language stimulation than white children at a statistically significant level at 24 months (.29 SD less than white children at $p < .10$) and 54 months of age (.42 SD less than white children at $p < .05$), with 36 months also trending towards less stimulation (.22 SD less than white children). As has been shown in other studies, structural factors are also associated with language stimulation. Higher child-caregiver ratios in particular were associated with less language stimulation.

Separating Evocative Effects from Environmental Causation

Even though evidence emerged, especially at 15, 24 and 54 months, that children do appear to shape the quality of care they receive in child care, at least insofar as language stimulation is concerned, it would be a mistake to conclude on the basis of this report that nonexperimental studies of child care effects are severely misestimating effects of child care by generally failing to take into consideration evocative child effects. Nevertheless, it remains the case that the small to modest effects of child care quality (i.e., language stimulation) detected in the NICHD SECC may represent some overestimate of child care influences.

The primary purpose of this study was to examine whether child effects on child care exist in the NICHD SECC. I find evidence that these child effects on quality of care, although small, are real, may differ by the age of the child, and can operate in multiple directions. One of the most important features, indeed strengths, of the NICHD SECC with respect to the purposes to which I put it is that it measured the *individual experience* of children. Rather than assessing overall classroom quality, child-care observations in this research project focused upon the immediate “psychological nutrients” provided by caregiver(s) to each target child. What was important was not whether a caregiver was generally stimulating, but whether the particular child enrolled in the study experienced a linguistically rich care environment. Recall in this regard that the predicted outcome was not an index of language stimulation at the level of the classroom or group, but of that experienced by the individual child. Such an approach to measurement seems most appropriate for evaluating and detecting child effects.

Although the present effort extends research on child effects and on the determinants of the quality of child care, it is not without limitations. Perhaps most notably, the study dealt only with assessed cognitive-linguistic ability and language stimulation. It should thus not be presumed that conclusions drawn from this work, either about child effects on caregiver behavior or of the extent to which detected child-care effects may actually reflect child effects, generalize to other features of child care (e.g., discipline). Moreover, the limits of nonexperimental work must be acknowledged when it comes to drawing causal inferences pertaining to child or child-care effects. Indeed, an evocative response based on children's characteristics might be best measured in a laboratory setting under controlled conditions, particularly conditions in which child behavior (or perceived child behavior) could be experimentally manipulated.

Finally, it seems possible that evocative effects may be stronger in some child-care settings than others. Although I failed to find statistically significant interactions between the type of care--center vs. home-based--it remains possible that interactions between children and characteristics of centers that were not examined in this study are important. Further study is needed to examine whether child-environment interactions vary across different contexts.

Implications for Research

Quite some time ago now Bell (1968) and Scarr and McCartney (1983) advanced arguments pertaining to how children influence their own development—by shaping the contexts of their development and thus their developmental experiences. Today most students of child development acknowledge the reality of child effects. Even an environmental theorist such as Bronfenbrenner (1979) attributed an important role to children in shaping their own environment, as do all other "interactionists", virtually by definition. Yet, decades since child effects have come to be part of the developmental lexicon, it remains the case that they are rarely entertained in discussions of child care research and child care interventions.

The positive evocative response I found at earlier ages provides one potential pathway by which the Matthew Effect (Merton, 1968) – "To all those who have, more will be given; but from those who have nothing, even what they have will be taken away" – may function. That is, children who are developmentally more advanced are spoken to more often, which in turn may further accelerate their language development, raising at least the risk that selection can be misinterpreted as causation. Just as important is the finding from this work that the Matthew Effect does not apply to all characteristics or at all time periods. Recall that children with *larger* vocabularies at age three actually received *less* verbal stimulation than their less linguistically skilled peers when 4.5 years of age. These results not only suggest that direction of evocative effects should not be presumed, but that for sake of accuracy, researchers should control for child effects when modeling child care quality at the child-level. Failing to do so could result in biased estimates of rearing effects.

My findings carry implications for the design of early child care interventions and for the training of child care workers. Caretakers should be made aware of any influence that children's behaviors may have on their own way of responding to them. The evocative influences of 15 month Bayley scores on the language stimulation environment at 15 and

24 months, the 24 month Bayley scores on the language stimulation environment at 24 months, and the change model between 15 and 24 months, are particularly concerning as a large literature suggests that language input these months are critical for language development and are when the “language explosion” occurs. To the extent that caretakers are speaking less to children with less developed language and cognitive skills, this can influence children’s language growth trajectories and may widen earlier inequalities in language or cognitive skill.

CHAPTER THREE: CHILDREN AS HOME-MAKERS: CHILD EFFECTS AND THE HOME LEARNING ENVIRONMENT

The study of family socioeconomic conditions and child development is at an exciting crossroads. Over the last half-century, a major research effort has gone into describing and understanding the role family economic (Elder, 1998; Duncan & Brooks-Gunn, 1997), class (Lareau, 2003), work (Menaghan & Parcel, 1991), education (Magnuson, 2002) language (Hart & Risley; Hoff, 2003), and home learning (Bradley & Corwyn, 2003) contexts play in shaping child growth and development. However, some of this work has been critiqued by researchers concerned that observed associations between home environments and children's outcomes are not causal, and instead are due to pre-existing differences between parents, children, or their environments (Scarr & McCartney, 1983; Duncan, Magnuson, & Ludwig, 2004; Rowe, Woulbroun, & Gulley, 1994).

In addition, developmentalists have argued that socioeconomic and child development research needs a more careful consideration of the ways in which children themselves interact with and influence their environment (Lerner, 2003; Bronfenbrenner & Morris, 1998; Magnusson & Torestad, 1992). Having a better understanding of how children influence their own home environments may be crucial for understanding the differential social risk experienced by children from disadvantaged backgrounds (Conger & Donnellan, 2007; Lerner, 2003; Rutter, 2003). This suggests that research on home conditions and child development should not only *control* for pre-existing child and family characteristics, but in fact make child effect processes, endogeneity processes, and other selection processes *central* to the research effort (Conger & Donnellan, 2007).

Of any of the often-measured characteristics of family socioeconomic status, the measure of the home learning environment (HOME, Caldwell & Bradley, 1979) might be the most predisposed to be influenced by the child himself, as it includes assessments of items that might vary on account of the parent responding to a child's proclivities, interests, or problems. Items that make up the measure include: how often does the child get out of the house?; how many books does the child have?; and, does the child have use of a tape/record/CD player(depending on the version of the measure)? A child who is very active might be much more likely to have a parent who makes an effort to get him out of the house; likewise, a child who displays enthusiasm about books or music might be more likely to receive them. Behavioral genetic findings suggest that this might indeed be occurring: research comparing the home environments of children of varying levels of genetic relatedness demonstrate that the HOME measure is moderately "heritable" (a heritability measure of ~40%); identical twins are more likely than fraternal twins, who are more likely than adopted siblings, to be "exposed" to a similar quality of home learning environment (Braungart, Fulker, & Plomin, 1992). Yet, the HOME measure is nearly always modeled as an environmental variable, exogenous to child characteristics.

Few researchers have tested whether there may be evocative effects of child cognitive characteristics on the home learning environment itself, although some have speculated as such. For example, Scarr (1996) argued that "more intelligent children naturally evoke and select more intellectually stimulating environments than less able children." Yet, she fails to cite any studies that support this assertion, and I have not found any studies that specifically test this hypothesis. Although a recent volume on socioeconomic status and child development included a summary chapter that emphasized a developmental systems and interactive perspective in understanding effects of the socioeconomic context on child development, none of the authors in that volume explicitly tackle how children themselves might influence SES-related measures of the environment. Child effects on the home environment can be controlled for statistically if researchers use fixed effects (Votruba-Drzal, 2003) or natural experiment models (Magnuson, 2002), but more often than not, cross-sectional and even longitudinal correlational research do not statistically or explicitly model putative child effects.

More is known about how other family characteristics influence the home environment. Parental socioeconomic factors are the most important influence on the quality of the home environment. Children living in low-income families, single-parent families, families with many children, or families whose mothers have low levels of academic aptitude or education tend to have less stimulating home learning environments (Votruba-Drzal, 2003; Baharudin & Luster, 1998; Menaghan & Parcel, 1995). Results for maternal employment are mixed, with some finding maternal employment improving cognitive simulation (Menaghan & Parcel, 1991), while others have not (Miller & Davis, 1997). A few, non-cognitive, child characteristics have been examined as predictors of the home environment. Research has shown that girls receive more cognitive stimulation than do boys (Garrett, et al., 1994; Miller & Davis, 1997). Health problems, developmental delays, and low birth weights are associated with worse home environments (Lee &

Barratt, 1993; Affleck, Allen, McGrade, & McQueeney, 1982), which could represent a child evocative effect, although Bradley, Rock, Caldwell, and Brisby (1989) found no difference in overall HOME or subscale scores when comparing their small sample of normal and handicapped infants.

No research of which I am aware, however, has explicitly examined whether children's cognitive competencies can influence the home learning environment. Related research would suggest that they might. The first study in this dissertation finds that younger children with more advanced developmental skills evoke more language stimulation in child care environments, although results were mixed for older children. Bornstein (1985) found that infant attention span at four months of age relates to the degree to which mothers encourage their child's attention at 12 months of age, suggesting that infant attentional abilities can evoke differential levels of parental attention. Heckhausen (1987a, 1987b) also found that mothers adapt behavior to their infant's level of development.

In the Abecedarian project, Ramey et al. (2002) found evidence for experimental impacts on child evocative behaviors. The children in the experimental group interacted differently with their mothers at twenty months and were comparable to middle class infants in their use of "requesting behaviors." At thirty-six months, experimental children were four times more likely to ask to read books or play games and played with their moms twice as long than control-group children. This suggests that the intervention may have changed child evocative behaviors, increasing the propensity of children to reach out to their environment and induce stimulation.

The current study

In this study, I address the following questions. First, do child cognitive skills evoke differential levels of cognitive stimulation at home? Based on findings from my first essay, as well as other research relevant to child evocative effects, I hypothesize that they will. Second, does the evocative response vary by age? I hypothesize that evocative effects from child cognitive skills may be more strongly positive among young children, but when children are of school-age, parents might “negatively” respond to children’s lower cognitive skills by increasing the stimulation available in the home environment. That is, more advanced cognitive skills will evoke more stimulating home environments when children are younger, but by age seven or eight, *less advanced* cognitive skills will actually evoke more stimulating home environments. Particularly among older children and adolescents, children with more school problems receive more help at home (Muller, 1995; Natriello & McDill, 1986). Third, does the response vary by gender? Based on work by economists, who have found a marginally higher level of parental investment in boys (Lundberg, 2005), I hypothesize that parents will have a stronger evocative reaction to boys’ cognitive skills than girls, and invest more in high-scoring sons than high-scoring daughters. Fourth, does the evocative response vary by parental income or education? I hypothesize that the evocative response will be stronger for children in higher income families and for child in families with more education. Such parents have more resources to draw from when attending to a child’s abilities and nurturing his interests. Lareau’s work (2003) suggests that middle-class parents are more likely to manage their children’s environments to “cultivate” their children’s reasoning ability, opinions, talents, and skills.

Other research has shown that more advantaged mothers are more responsive to their children when they talk (Hoff, 2003), while persistent poverty and its co-factors have been shown to reduce responsive and stimulating care (Conger, Conger, & Elder, 1997; McLoyd, 1998; Luster & Dubow, 1990).

Analytic approach

My goal is to isolate the evocative effects of child cognitive development on the home environment. My model assumes that the home environment is influenced by the child's past and current cognitive and linguistic propensities, other factors related to the child, and factors related to the family. The overall model is:

(3.1) $$\mathbf{HOME_{ti} = \beta_0 + \beta_1 COG_{ti} + \beta_2 CHILD_i + \beta_3 CHILD_{ti} + \beta_4 FAM_i + \beta_5 FAM_{ti} + e_i}$$

In equation 3.1, child *i*'s home learning environment (HOME) at time *t* is a function of a child's current cognitive capabilities (COG), and time-invariant and time-variant child and family factors. I model children's cognitive capabilities using two types of cognitive scores: both Math and Reading PIAT scores, or the child's PPVT score (equations 3.1a and 3.1b).

(3.1a) $$\mathbf{HOME_{ti} = \beta_0 + \beta_1 READING\ PIAT_i + \beta_2 MATH\ PIAT_i + \beta_3 CHILD_i + \beta_4 CHILD_{ti} + \beta_5 FAM_i + \beta_6 FAM_{ti} + e_i}$$

(3.1b) $$\mathbf{HOME_{ti} = \beta_0 + \beta_1 PPVT_i + \beta_2 CHILD_i + \beta_3 CHILD_{ti} + \beta_4 FAM_i + \beta_5 FAM_{ti} + e_i}$$

I use four different empirical methods to model the evocative effect of child cognitive characteristics (COG): OLS models with lagged-dependent variables, individual fixed effects, family fixed effects, and multilevel models. Each approach has advantages and drawbacks, but I will look for the pattern of results to be robust across these multiple specifications.

OLS model with lagged-dependent variable

$$\textbf{(3.2)}\ \mathbf{HOME_{ti} = \beta_0 + \beta HOME_{t\text{-}1i} + \beta_1 COG_{ti} + \beta_2 CHILD_i + \beta_3 CHILD_{ti} + \beta_4 FAM_i + \beta_5 FAM_{ti} + e_i}$$

In equation 3.2, the home environment (HOME) at Time 2 for child i is expressed as a function of child developmental characteristics at Time 2 (COG), controlling for a Time 1 measure of the home learning environment (HOME). Including the Time 1 home environment outcome controls for time-invariant differences between children's home environments (both measurable and not) that were present at the first wave of data collection. To further limit the possibility that children with particular individual or family characteristics are selected into home environments of varying quality, I include measures of child (CHILD) and household (FAM) covariates – both time invariant and time variant factors.

This approach makes the assumption that unobserved, confounding variables have similar impacts on both early and later outcomes and that the error in assessment at both ages is random. To the extent that the impact of child and family characteristics on child cognitive/language development and the home environment differ between the two points in time, this may bias estimates. The results should be interpreted in light of this limitation.

I also perform subgroup analyses using the lagged-OLS regression. I compare the evocative effect by younger and older (5-10 years old versus 10-15 years old) children, males versus females, low and moderate versus high income (less than $40,000 versus more than $40,000), and low versus high maternal education (high school education or less versus more than a high school education). The analyses were tested for significance by running models with interaction terms between the subgroup indicator and all variables in the model.

Individual fixed effect model

With the individual fixed effect model, I difference across time within individuals. The individual fixed effect model begins with the overall model:

$$\textbf{(3.1) } HOME_{ti} = \beta_0 + \beta_1 COG_{ti} + \beta_2 CHILD_i + \beta_3 CHILD_{ti} + \beta_4 FAM_i + \beta_5 FAM_{ti} + e_i$$

Where e_i includes the unobserved child and family effect. I am concerned about this error being systematically related to the association between child cognitive ability and the home environment. With this in mind, note that the evocative effect at time *t-1* is:

$$\textbf{(3.3) } HOME_{t-1\,i} = \beta_0 + \beta_1 COG_{t-1i} + \beta_2 CHILD_i + \beta_3 CHILD_{t-1i} + \beta_4 FAM_i + \beta_5 FAM_{t-1i} + e_i$$

By differencing within individuals (subtracting equation 3.3 from 3.1), I remove the all time invariant child and family factors ($CHILD_i$ and FAM_i) and am only left with time variant factors related to the child and family.

$$\textbf{(3.4) } \Delta HOME_i = \beta_0 + \beta_1 \Delta COG_i + \beta \Delta \text{time varying child and family factors}_i + \Delta e_i$$

In equation 3.4, a change in a child's HOME score across two points in time is the result of a change in his cognitive scores and changes in other time-varying factors related to the child and his family. The time-varying factors include family factors such as household income, maternal employment, and family structure, which may and often will vary over time and can potentially influence the association between a child's cognitive development and his home learning environment. Such time-variant factors, if omitted from the model, might bias coefficients to the extent their influences varies by child age. For example, we know that family income has a larger effect on younger children's cognitive development compared to older children (Clark-Kauffman, Duncan & Morris, 2004), thus we should include such time-varying factors in our models.

Family fixed effects

Another way to "difference out" fixed family factors that putatively influence the quality of the home learning environment is to compare children within the same family.

(3.5) difference sib HOME = β_0 + $\beta_1$difference in sib COG + $\beta_2$difference in sib-varying factors + β_3 difference in sibs family time-varying factors + diff sib e_i

For the family fixed effects model (equation 3.5), I regress the difference between siblings' average home environment scores across all measurement occasions on the difference between their average cognitive or achievement scores across all measurement occasions, as well as differences in any child- or family-related factors that vary across children within the same family. I use information from all measurement occasions because a child's *average* HOME score and *average* cognitive score across numerous points in time may best capture their latent HOME and cognitive scores. Differences in family-invariant factors, such as maternal race, maternal AFQT score, or other family factors that are equally shared by different children in the same family, drop out of the model. Again, however, family characteristics such as income or maternal education that may vary for differently-aged children in the family must be included in the model. These include family marital status, income, maternal education, family urban status, number of children in the family, and maternal age. Families that have only one child are not included in this analysis, and I use the first two children within a family for this analysis.

Multilevel models

The class of models known as multilevel or hierarchical linear models (HLM) are another tool with which I can test the evocative effects hypothesis. I use multilevel modeling to complement my three other types of analyses. Although the nature of my outcome (a standardized measure of HOME) limits my ability to employ growth curve modeling, I am still able to take advantage of multi-level modeling with time-varying covariates on a repeated measure outcome.

For example, with multilevel models, data from all sample members contribute to estimates, regardless of how many waves an individual participates in the study (Singer & Willett, 2003). Although they provide less, or no, information about within-person variation they can still contribute to the estimates of the fixed effects. Multilevel models are also valuable because they explicitly model the dependence among residuals (most importantly, correlating error over time within the same child) instead of merely treating the dependence among residuals as a nuisance, such as correcting for them with the Huber-White correction.

A particular type of multilevel modeling that is often used to model change within an individual over time is growth curve modeling. Singer and Willett (2003) recommend that to most effectively use growth curve modeling, a study must have the following attributes: 1) three or more waves of data, 2) a sensible metric for clocking time, and 3) an outcome which has values that change systematically over time. The NLSY data set fulfills the second criterion, but the first and third criteria present challenges.

I lack three waves of data for a substantial minority of the children in the sample, which will increase the size of the standard errors for my estimates. Of the total 8,207 children: 1,336 children received one PIAT assessment; 1,746 children have two assessments; 2,172 children have three assessments; 2,400 children have four assessments, and 553 children have five assessments.

As noted with the third criteria, growth models are designed for continuous outcomes which have values that change systematically over time (Singer & Willett, 2003). My outcome variable, the cognitive subtest of the HOME, is standardized by child age such that there is no developmental component to the measure. This is because the items that make up the HOME measure differ by child age, which means that the HOME must be standardized by child age (standardized within single year intervals – see the Methods section for more details) to facilitate comparison across age groups; the HOME was not designed to measure change in the home environment over time in the way height or weight measurements, or math tests, can assess developmental growth.

However, multilevel modeling can still provide information about what influences baseline levels of the HOME measurement, and can shed light on which time varying predictors of interest (including changes in child cognitive skill) influence relative *rank order* changes in the standardized HOME over time and effectively model HOME, as well as other time-varying covariates.

An issue facing all longitudinal analyses is concern about how to deal with time-variant characteristics – particularly ones that may have reciprocal relationships with the outcome variable (such as my predictor of interest – child cognitive and language ability). Although multilevel models with time-varying predictors and covariates are occasionally offered as solutions to the reciprocity problem, in fact they do not solve this problem any more than any other type of cross-sectional modeling (Singer & Willett, 2003; Raudenbush, 2001). Singer and Willett (2003) suggest that one way of modeling reciprocal, time-variant characteristics is using the lagged measure of all time-variant measures, thereby ensuring that it is not currently being influenced by the outcome variable. Another way of modeling is to use change scores to predict outcomes (Raudenbush, 2001; Rutter, 2003). I employ both of these methods in my multilevel models.

With these caveats in mind, I model the associations between child cognitive scores and the home learning environment over time in four ways with multilevel modeling: with contemporaneous measures of cognitive skills, lagged measures (prior time point) of cognitive skills, both contemporaneous and lagged measure of cognitive skills (to examine which is more highly associated with the HOME), and change in cognitive skill between two measurement points. For this set of analyses, I use the reading and math PIAT scores as a measure of child cognitive skill, rather than the PPVT, because the PIAT is assessed at more measurement occasions than the PPVT.

My multilevel model includes both Level 1 predictors (child reading and math scores, as well as within-child time-varying covariates at the child and family level) and Level 2 predictors (between child covariates). My level 1 model is as follows (equation 3.6)

(3.6) $\mathbf{HOME}_{ij} = \pi_{0i} + \pi_1 \mathbf{Math\ PIAT}_{ti} + \pi_2 \mathbf{Reading\ PIAT}_{ti} + \pi_3 \mathbf{Child\ age}_{ti} + \pi_4 \mathbf{Family\ time\text{-}varying\ characteristics}_{ti} + \varepsilon_{ij}$

I let $HOME_{ij}$ be a result of child i's mean level HOME score (π_{0i}), as well as other time-varying characteristics, including the predictors of interest Math and Reading PIAT scores, child age, and other family time-varying characteristics, including maternal age, maternal education, income, marital status, urban residence, family size.

My level 2 equation is the following (equation 3.7). I predict π_{0i} with child and family Level 2 covariates.

(3.7) $\pi_{0i} = \gamma_{00} + \gamma_{01}\mathbf{CHILD} + \gamma_{02}\mathbf{FAM} + \varepsilon_{ij}$

Here, the mean HOME score is predicted by time-invariant child predictors gender and race, and the time-invariant family predictor maternal AFQT score.

All of the continuous variables are centered on the sample mean, so the estimated intercept (π_{0i}) reflects the initial HOME score for a child with average values for continuous variables and zeros for all dichotomous indicators (Singer, 1998). The full model (substituting the right side of equation 3.7 for π_{0i} in equation 3.6) results in the following:

(3.8) $HOME_{ij} = \pi_1$Math $PIAT_{ti} + \pi_2$Reading $PIAT_{ti} + \pi_3$Child $age_{ti} + \pi_4$Family time-varying $characteristics_{ti} + \varepsilon_{ij} + \gamma_{00} + \gamma_{01}CHILD + \gamma_{02}FAM + \varepsilon_{ij}$

As described earlier, I use four different models to predict $HOME_{ij}$:

(3.9) Contemporaneous Model: $HOME_{ij} = \pi_1$Math $PIAT_{ti} + \pi_2$Reading $PIAT_{ti} + \pi_3$Child $age_{ti} + \pi_4$Family time-varying $characteristics_{ti} + \varepsilon_{ij} + \gamma_{00} + \gamma_{01}CHILD + \gamma_{02}FAM + \varepsilon_{ij}$

In equation 3.9, I predict HOME using contemporaneous measures of children's math and reading skills.

(3.10) Lagged Model: $HOME_{ij} = \pi_1$Math $PIAT_{t-1i} + \pi_2$Reading $PIAT_{t-1i} + \pi_3$Child $age_{ti} + \pi_4$Family time-varying $characteristics_{ti} + \varepsilon_{ij} + \gamma_{00} + \gamma_{01}CHILD + \gamma_{02}FAM + \varepsilon_{ij}$

In equation 3.10, I predict HOME using prior measures of children's math and reading skills.

(3.11) Lagged and Contemporaneous Model: $HOME_{ij} = \pi_1$Math $PIAT_{ti} + \pi_2$Reading $PIAT_{ti} + \pi_3$Math $PIAT_{t-1i} + \pi_4$Reading $PIAT_{t-1i} + \pi_5$Child $age_{ti} + \pi_6$Family time-varying $characteristics_{ti} + \varepsilon_{ij} + \gamma_{00} + \gamma_{01}CHILD + \gamma_{02}FAM + \varepsilon_{ij}$

In equation 3.11, I predict HOME using both lagged and contemporaneous measures of children's math and reading skills.

Method

Sample

This study uses the Children of the National Longitudinal Study of Youth (C-NLSY). The NLSY is made up of a sample of women who were all 14 to 21 years of age on December 31, 1978. Starting in 1986, study organizers attempted to assess all biological children of NLSY79 mothers, although in 1988 and beyond the sample of children eligible for assessment was restricted to children living part or full-time with their mothers. Every two years after this through 2004, the children have been followed and assessed. In 2004, a total of 11,428 children had been identified as having been born to the original 6,283 NLSY79 female respondents.

Most of the women interviewed have had more than one child, including a rather large sample of women who have had three or more children. When appropriate weights are applied, NLSY79 women have had on average about 1.9 children, which is estimated to be more than 90 percent of their ultimate childbearing. Although in earlier waves, the sample of children were disproportionately born to lower SES mothers, later waves have balanced this out and the overall sample is now quite representative of children born to women who were in the United States in 1979 and aged 14 to 21 years. The C-NLSY is well-suited to the present study because it includes repeated measures of the home learning environment at every assessment, repeated measures of children’s cognitive development and academic achievement at several different ages (which allows for within-child analyses), and because every child in a family was assessed (which allows for within-family analyses).

Given that the child interviewing process began with the 1986 interview round and has continued on a biennial basis through 2004, many children have been assessed multiple times. In the present study, my dependent variable of interest is a measure of the home learning environment, the HOME. Nearly all of the children in the study received two or more assessments of their home learning environment.

Many women gave birth to multiple children during this 12-year time period, so data on these children were not independent. Huber-White statistical techniques were used to adjust for autocorrelation in the data for the OLS regressions. All analyses were weighted using the child sampling weights assigned by the CHRR to each child at the time of the HOME environment assessment. Weighted, this sample is nationally representative of all children who were born to women between 14 to 21 years old in 1979. Characteristics of the final sample of children and mothers are presented in Table 3.1.

Instruments

Multiple field instruments are used to collect information from and about the NLSY79 children concerning their health, aptitudes, achievement, attitudes, and behavior. A Mother Supplement (MS), given to the mother for each child, contains mother-report assessments and questions about the home environment, health, school, and family background. The Child Supplement (CS) is a questionnaire administered by the interviewer. It is used by the interviewer to verify age and grade, measure the child's height and weight, complete the interviewer-administered assessments, and to get reports from school-agers about their schoolwork, work for pay and religion. Interviewers also record observations of the home environment and selected maternal and child behaviors.

Measures

Outcome measure. To capture the nature and quality of the child's home learning environment, I use the cognitive stimulation component of the HOME Short Form, which is derived from the HOME (Home Observation for Measurement of the Environment) Inventory (Caldwell & Bradley, 1984). The HOME-SF is about half as long as the original HOME Inventory, an adaptation necessitated by survey time and cost constraints. More than half of the HOME-SF's items are multi-response maternal reports that were reworded, with the assistance of the instrument's designers, from the original HOME Inventory's dichotomous observer ratings. The instrument is administered in Spanish if that is the preferred language of the mother. The HOME has been shown to be a better predictor than any other existing parenting measure of children's cognitive outcomes (Magnuson, Duncan, & Kalil, 2003; Bradley & Corwyn, 2003).

All children under the age of 15 living with their mothers were eligible for the HOME assessment for the NLSY (many children over the age of fifteen also received the HOME assessment). Thus, children born by the 1988 survey date may have seven rounds of HOME scores available, although most children do not have that many. The items that mothers complete are dependent on the age of the child: children under age 3 years, 3 through 5, 6 through 9, and 10 and over follow different question sequences. Whereas the raw scores are specific to a child's age at a particular survey point, a single set of normed scores is created for each survey round, regardless of the child's age.

In addition to the overall HOME-SF score, there are two HOME-SF subscores: a cognitive stimulation and emotional support score. The cognitive stimulation subscore is my key outcome of interest for this study. The score is derived from a battery of questions that vary somewhat depending on the child's age.

For children under age 3, the cognitive subscale is made up of the following questions asked of the mother: How often does child have a chance to get out of the house? About how many children's book does child have? How often do you get a chance to read to child? How often do you take child to the grocery store? About how many, if any, cuddly, soft, or role-playing toys does child have? About how many, if any, push or pull toys does child have? How often do you spend time teaching your child new skills? The interviewer also reported on whether, during the interview, the mother provided toys or interesting activities for child and whether the child's play environment is safe.

For children aged 3-5, the cognitive subscale is made up of the following questions asked of the mother: How often do you read stories to child? About how many children's books does child have? About how many magazines does your family get regularly? Does child have the use of a CD player and at least 5 children's records or tapes? Do you or someone else help child with numbers? Do you or someone else help child with the alphabet? Do you or someone else help child with colors? Do you or someone else help child with shapes and sizes? How often does a family member get a chance to take child on any kind of outing? How often has a family member taken or arranged to take child to any type of museum? The interviewer also reported on whether the child's play environment is safe, whether the interior of the home is dark or monotonous, whether all visible rooms of house/apt are reasonably clean, and whether all visible rooms of house/apt are minimally cluttered.

For children aged 6-9 years, the cognitive subscale is made up of the following questions asked of the mother: About how many books does child have? How often do you read aloud to child? Is there a musical instrument that child can use here at home? Does your family get a daily newspaper? How often does child read for enjoyment? Does your family encourage child to start and keep doing hobbies? Does child get special lessons or belong to any organization that encourages activities such as sports, music, art, dance, drama, etc? How often has a family member taken or arranged to take child to any type of museum? How often has a family member taken or arranged to take child to any type of musical or theatrical performance within the last year? When your family watches TV, do you or father discuss programs with her? The interviewer also reported on whether the interior of the home is dark or monotonous; whether all visible rooms of house/apt are reasonably clean; whether all visible rooms of house/apt are minimally cluttered; and whether child's play environment is safe.

For children aged 10-14 years, the cognitive subscale is made up of the following questions asked of the mother: About how many books does child have?, Is there a musical instrument that child can use here at home? Does your family get a daily newspaper? How often does child read for enjoyment? Does your family encourage child to start and keep doing hobbies? Does child get special lessons or belong to any organization that encourages activities such as sports, music, art, dance, drama, etc? How often has a family member taken or arranged to take child to any type of museum?, How often has a family member taken or arranged to take child to any type of musical or theatrical performance within the last year?, When your family watches TV, do you or father discuss programs with her? The subscale is also made up the following items reported by the interviewer: Is the interior of the home is dark or monotonous? Are all visible rooms of house/apt are reasonably clean? Are all visible rooms of house/apt are minimally cluttered? Is the child's play environment is safe?

As noted previously, a single set of normed scores is created by the NLSY for each survey round, regardless of the child's age. The average score should be 1000, with a standard deviation of 150. Upon examining the scores in my final sample, however, I noticed that the mean score by child age was lower than 1000, and in addition, that older children had lower standardized scores. This is the case especially within the age 10 and above group. On average, ten year olds had HOME scores about 987, while thirteen year olds scored 958, and fifteen year olds scored 934 (Table 3.2). Thus, I re-standardized the raw HOME scores by child age, removing this age trend from the scores.

Independent variables of interest.

My independent variables of interest include various measures of the child's cognitive development or academic skills. The *Peabody Picture Vocabulary Test-Revised* (PPVT-R) measures the hearing vocabulary knowledge of children whose age is three and above. The PPVT-R was administered to children age 4 and 5 or 10 and 11 starting with the 1996 survey round. The *Peabody Individual Achievement Test (PIAT) Math* (American Guidance Service) is a PIAT subtest that offers a wide-range measure of achievement in mathematics for children aged five and older. The *PIAT Reading Recognition and Reading Comprehension Test* assesses the attained reading knowledge and comprehension of children aged five and older. I use the PIAT reading comprehension scale for this essay because I hypothesize that reading comprehension (a practical understanding of a text) provides a more likely candidate for the evocative response than mere reading recognition (decoding a text) skills.

The reading comprehension scale consists of 64 items that measure children's practical reading ability. Only children who answered more than 19 questions correct on the reading recognition test were given the reading comprehension test. Children who scored less than 20 were assigned their reading recognition score as a reading comprehension score. (The reading recognition test consists of 84 items that assess children's oral reading skills such as word recognition and pronunciation ability.) At age six years about 85% of children answered fewer than 20 reading recognition questions correctly, but by age eight this had declined to 12%, and it was less than 2% for older children. For all three measures, age-standardized scores were created from raw scores (number of correct answers provided) using three month age-increments and all available observations in the NLSY. The standardized scores have a full sample mean of 0 and standard deviation of 1.

Control variables

The NLSY surveys collect information on many relevant background characteristics of the child and family. Child-level characteristics include child age, gender, race/ethnicity, birth weight, and birth order. Family-level, time-invariant characteristics include a measure of maternal cognitive ability at age 18 (the Armed Forces Qualifying Test or AFQT), and average maternal grandparent education. Family-level, time-variant characteristics include maternal age, family income (scaled in $10,000 increments), maternal education, marital status, total number of household members, total number of children of the maternal respondent in the household, and whether the family lives in an urban area. These covariates were selected for the model because prior research suggests that they may influence the quality of the home learning environment.

Weights

The sampling weights adjust the unweighted data for sample attrition of mothers and their children since the first survey round (1979) and the sample reduction due to the loss of the military and economically disadvantaged white oversample and adjust the sample for the over-representation of black and Hispanic youth. Using weights translates the unweighted sample of children into a population that represents all children who have been born by that date to a nationally representative sample of women who were 14 to 21 on December 31, 1978.

Results

Cross-sectional associations

First, I examine correlations between different variables (Table 3.3). The cognitive subscale of the HOME (labeled as HOME in the table) is highly correlated with all cognitive assessments (correlation of .40 with PIAT math, .41 with PIAT reading, and .48 with PPVT, all significant at $p < .01$). This correlation could be the result of the HOME influencing cognitive scores, cognitive scores influencing the HOME, or some other variables influencing both. The cognitive scores are all highly correlated with various child and family characteristics. All three cognitive scores are negatively associated with child age (older children in the sample are more likely to have been born to mothers of low socioeconomic status), child being Black or Hispanic, birth order, and number of children in the family, and positively associated with maternal age and aptitude, and marital status, income, and maternal education

The home learning environment is negatively associated with the child being Black (r= -.22) or Hispanic (r= -.16) and is negatively associated with higher birth order and number of children in the family. The HOME is positively associated with maternal cognitive scores (r= .43), and being married (r=.34), higher income (r=.28), and more parental education (r= .34). The measure of the home learning environment is also highly correlated with itself across time, although associations decline at greater time intervals (Table 3.4). For example, measures of the home learning environment that are taken at two years apart correlate around .55, while those taken ten to twelve years apart correlate around .32. HOME scores are also highly correlated across children in the same family (Table 3.5), although they are somewhat more highly correlated between children close in rank (e.g., first-born and second-born are correlated at .70 while first-born and fourth-born are correlated at 0.64.)

Another question of interest is whether *differences* within a family in scores are positively correlated with math and reading scores. Such a correlation might be indicative of a child evocative effect, as it would mean that, within the same family, the child with the more advanced skills is exposed to a better home environment. If the home environment is due only to time-invariant parental factors, such a correlation would not occur. Table 3.6 indicates that the difference in sibling Reading PIAT scores is correlated .16, the difference in Math PIAT scores is correlated .15, and the difference in PPVT scores is correlated .16 with differences in the home learning environment.

OLS regression with lagged dependent variable

Next, I examine the evocative effect of three different measures of cognitive development/academic achievement using an OLS regression model with lagged dependent variables (Table 3.7). Each time point is considered a separate observation, so if a child has three observations (t-1, t, and t+1), he would be included twice in the OLS lagged analysis (standard errors are adjusted with the Huber-White correction to account for non-independence). These models include a battery of child and family controls, as well as a prior measure of the home environment. For Model 1, I find that a 1 SD higher Math PIAT score is associated with a .08 SD higher HOME score, controlling for the prior measure of HOME. In Model 2, a 1 SD higher Reading PIAT score is associated with a .08 SD higher HOME. In Model 3, a 1 SD higher PPVT score is associated with a .12 SD higher HOME score. In Model 4, I include both Math and Reading PIAT scores together, and find that a 1 SD higher Math PIAT score is associated with a .05 SD higher HOME score, while a 1 SD higher Reading PIAT score is associated with a .06 SD higher HOME score, controlling for the prior measure of HOME. This suggests that both reading and math proficiencies contribute to the evocative effect, although the coefficient on the reading score is slightly higher than the math score. I also ran models (not shown) that examined the interaction of math and reading scores, but the coefficient on this interaction term was small and nonsignificant.

Other child characteristics play important roles in predicting HOME. Being male is associated with about .11 SD lower HOME for all three models. Child minority status is also highly associated with lower HOME scores. Across the three models, being black is associated with about a .07 SD lower HOME score, while being Hispanic is associated with about a .12 SD lower HOME score. Birth order is also associated with lower HOME scores. For each consecutive child, the HOME is lower by about .02 SD due to birth order and .02 SD due to number of children in the family. (When only one of these variables is included in the regression, the overall effect of birth order is .04 SD and the overall effect of total # of kids in the household is -.03 SD). Being of low birthweight has no influence on the quality of the home learning environment for two of the models, but for the PPVT model is actually associated with a .09 SD higher HOME score.

As has been noted in other studies, factors relating to the mother also influence the quality of the home learning environment. Increasing maternal age is associated with lower quality HOME. Each additional year of maternal age is associated with about a .01 SD decline in HOME, while each additional percentile rank on the AFQT test is associated with a .002 SD higher HOME. Each additional year of maternal education is associated with about a .03 SD higher HOME, while each additional year of *grandparent* education is associated with a .01 SD higher HOME. Being in a household with a married mother has a very significant influence on HOME, between .20 -.30 SD higher HOME. Each additional ten thousands dollars of income is associated with a .005 SD higher HOME. Urban residence is also associated with a higher HOME – between .06-.09 SD depending on the model.

Non-linear effects

I next ran the lagged OLS models with a quadratic functional form, as well as a categorical form, for the cognitive measure. If there are "increasing returns" on the evocative effect from cognitive skill, including an exponential coefficient will capture this effect. Table 3.8 summarizes these results. Overall, these models did not appear to perform better than the basic linear model. There does appear to be a non-linear relationship between Reading PIAT score and the HOME, in that the exponential term is negative and significant. This means there may be "diminishing returns" to higher reading PIAT scores. This is also apparent in the model using reading PIAT dummies as well, in that scores in the 75^{th}-100^{th} percentile do not evoke better learning environments than scores in the 50^{th}-75^{th} percentile; they are associated with a nearly identical .17 and .18 SD higher HOME score, respectively.

Sub-group models

In Tables 3.9-3.12, I examine whether the effect of child developmental competence on the HOME varies by child age, gender, maternal education, or family income, using the lagged-OLS model. In general, I did not find much evidence for substantial subgroup differences in the evocative effect.

In Table 3.9, older children who score 1 SD higher on the Reading PIAT evoke .07 SD better home learning environments, compared to younger children who evoke .04 SD (the difference is significant at $p < .05$). In contrast, the evocative effect did not significantly vary by child age for the Math PIAT or PPVT.

In Table 3.10, the evocative effect for girls' math scores is stronger than boys' math scores. Girls who score 1 SD higher on the Math PIAT evoke a .06 SD better home environment, compared to boys' .04 SD (significant at $p < .05$).

The pattern of evocative effects by maternal education is ambiguous (Table 3.11). I find that the evocative effect of reading scores is stronger for children whose mothers are less well educated. A 1 SD higher Reading PIAT score evokes a .04 SD better home environment for children whose mothers have 13 or more years of education, while it evokes a .08 SD better home environment for children whose mothers have less than 13 years of education (the difference is significant at $p < .05$). However, the evocative effect detected with the Math PIAT score was higher for children of mothers with more education (.06 SD vs. .03 SD). Finally, the evocative effect did not vary significantly by family income (Table 3.12).

Individual fixed effects

In Table 3.13, I present results from individual fixed effects regressions of child scores on the home learning environment. Recall that coefficients for the individual fixed effect regressions represent the influence of change in a child's cognitive or language scores regression on changes in his or her HOME learning environment. The individual fixed effects regressions are more than a simple first difference with this data, as many children have three or more assessment points. Overall, the measured evocative effects are smaller than the lagged OLS regression, but they remain positive and significant. For Model 1, I find that a 1 SD higher Math PIAT score is associated with a .02 SD higher HOME measure, while a 1 SD higher Reading PIAT score is associated with a .03 SD higher HOME. In Model 2, I find that a 1 SD higher PPVT score is associated with a .05 SD higher HOME score.

Family fixed effects

In Table 3.14, I present results from family fixed effects regressions on the home learning environment. Here, I examine whether differences in average cognitive scores from children in the same family are associated with differences in their average HOME environment. For Model 1, I find that a 1 SD difference in two children in the same family's Math and Reading PIAT scores is associated with a .05 SD difference in their HOME learning environments. In Model 2, I find that a 1 SD difference in a child's PPVT score is associated with a .09 SD difference in the HOME. The coefficients for the family fixed effects are between the size of the individual fixed effects and the lagged OLS models; somewhat smaller than the lagged-OLS results, but larger than the individual fixed effects coefficients.

Multilevel models

With the multilevel models, I model the influence of child cognitive scores (Reading and Math PIAT scores) on the HOME (Table 3.15). First, I ran an unconditional means model. Model 1 presents the results of fitting the unconditional means model to the data. Its one fixed effect, γ_{00}, the intercept, estimates the outcome's grand mean across all occasions and individuals. As expected for a standardized measure, it is approximately zero. Next, I examine the random effects. The estimated within-person variance is .57, while the estimated between-person variance is .41, and both are highly significant. This means that the average child's home environment varies over time and children differ from one another in their home environment[2].

In Model 2, I predict the HOME with current measures of child cognitive skills, along with a battery of controls. Here, a 1 SD higher Reading score is associated with a .08 SD higher HOME score, while a 1 SD higher Math score is associated with a .06 SD higher HOME.

Model 3 uses the prior measures of cognitive skills to predict home. Here, a 1 SD higher Reading and a 1 SD higher Math score are both associated with a .05 SD higher HOME score.

Finally, in Model 4, I include both prior and contemporary measures of cognitive skill. A 1 SD higher contemporaneous Reading score is associated with a .08 SD higher HOME, a 1 SD higher contemporaneous Math score is associated with a .05 SD higher

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[2] Although not shown here, I also examined the unconditional growth model; this model introduces the predictor "child age" into the level-1 submodel. As expected, the starting point is a HOME score of approximately 0, while the average decline is effectively zero. The level-1 residual variance, which summarizes the average scatter of an individual's observed outcome values around his or her own true change trajectory, did not decline at all from the unconditional means model to the growth model. This suggests that child age does not play a role in predicting a child's HOME trajectory over time. This is to be expected, given that the outcome of interest, the HOME, is standardized by child age. The population covariance of the level-2 residuals σ_{01} has an important interpretation in the unconditional growth model, because it quantifies the population covariance between true initial status and true change. This means that we can assess whether children who have higher initial HOME scores increase their HOME scores more or less rapidly over time. The covariance is approximately 0, so this suggests this is not happening. As there is no growth to predict, in the subsequent models, I remove the growth term from the model.

HOME, a 1 SD higher prior Reading score is associated with a .02 SD higher HOME, while a 1 SD higher prior Math score is associated with a .03 SD higher HOME.

Discussion

Based on a wide range of analytic techniques, my results suggest that children's cognitive and language proclivities influence their home learning environment. Children's math, reading, and vocabulary scores, as measured by standardized assessments, predicted the quality of their home learning environment using lagged dependent variable regression models, individual fixed effect models, family fixed effect models, and multilevel models.

The size of the effects do vary across the different models, although all are fairly small in size. They vary from .02 SD from the individual fixed effect models to .12 SD from the lagged regression. With the HLM model, I find a .08 SD effect on the HOME from a 1 SD higher Reading score, and a .06 SD effect on the HOME from a 1 SD higher Math score.

Which type of model, of the four that I tested, is most appropriate to capture the evocative effect? I argue that the individual fixed effects and family fixed effects are the most appropriate, and also more conservative, than the lagged-OLS models. The individual fixed effect concretely shows how a change in a child's cognitive score can evoke a change in his own home environment, and eliminates bias from child and family factors that are differenced out in the estimation. The family fixed effect is particularly appealing in that it identifies how different children in the same family can actually be exposed to different home environments, and not just because of differences in their parental circumstances, but because of the children evoking different home environments. It is a little more subject to bias than the individual fixed effect model due to factors that might vary between children within the same family (not just the evocative response) that are not explicitly modeled, but that might be leading to different levels of the HOME.

The multilevel model is appealing because it explicitly models the variance at different levels (within individual and between individuals) and models the change in rank order of individuals. Its results are similar to the other models. The HLM model that includes both lagged and contemporanoues measures of the Math and Reading PIAT tests shows that both lagged and contemporaneous measures remain significant despite the other being controlled for.

A major issue with this research endeavor is capturing the timing of the evocative response. The prior literature provided little guidance on how, if parents are actually responding to children's developmental capabilities, what sort of time-frame this occurs on. In addition, it is not even clear to what degree the HOME assesses only the *current* home environment versus a parent's report of longer-term aspects of the HOME. The assessment has questions that one mother might answer keeping in mind only the most current activities with her child, while another might answer along a longer time horizon. Certainly, the number of books or CDs a child has will be a reflection of a longer-term measure of a child's proclivities. In contrast, other items on the HOME cognitive scale are interviewer observations of parent-child interactions or parent behaviors towards the child. These items will likely be more strongly linked with current measures of a child's academic proclivities. The fact that both prior and contemporaneous measures of children's math and reading competencies predict HOME scores (as shown in the multilevel model equation 3.11) suggest that indeed both contribute to the evocative response.

Comparing *overall* levels of childhood HOME, between children, within a family (the family fixed effect model), is another way to estimate the evocative effect across a longer time period. More work is needed to verify the presence of the evocative effect, assess its size and importance, and pin down the timing of it.

In general, the size of the evocative effects did not vary very much by age, gender, or family socioeconomic status. This was surprising to me, given prior work suggesting that parents might react differently to children's proclivities based on other child or family factors. I should note, however, that there were substantial *main* effects of gender, and family socioeconomic status that played important roles in predicting the quality of the home learning environment. Controlling for all other factors, male children had HOME scores that were about .12 SD lower than girls, while maternal education, family income, and marital status also all played important roles in predicting the quality of the home learning environment. Interestingly, even living in an urban area compared to a non-urban area was associated with about a .08 SD. The evocative effect of a 1 SD increase in children's cognitive capacities was, overall, a bit smaller than some of the more important child and family attributes.

Theoretical implications

Human development theory has long emphasized the role culture, policies, neighborhood, and parents play in shaping home learning environments, but much less attention has been paid to the role children play themselves in influencing home environments. This study suggests that children's cognitive capacities do play a role in "home-making," and that children with stronger reading, math, or vocabulary skills evoke more stimulating home learning environments.

The results have implications for researchers who study the influence of the home learning environment on children's cognitive development. The results suggest that researchers need to model the HOME measure as an endogenous variable, shaped in part by children themselves.

The results also have implications for understanding the differential social risk experienced by children from disadvantaged backgrounds (Conger & Donnellan, 2007; Lerner, 2003; Rutter, 2003). Researchers on home conditions and child development should not only *control* for pre-existing child and family characteristics, but in fact make child effect processes, endogeneity processes, and other selection processes *central* to the research effort (Conger & Donnellan, 2007). More research is needed to examine how child evocative effects might influence other "environmental" variables, such as school climate, classroom instruction, time spent with parents, what parents do with their children, after-school activities or participation in youth clubs or sport teams. Thinking about such evocative child effects also pushes us to think more carefully about *parenting* as a construct. These results suggest that the HOME measure of the home learning environment may be capturing how parents react to their individual child's proclivities, strengths, or weaknesses rather than merely capturing the parent's inherent propensity to provide a particular level of stimulation given their economic or educational resources.

Too often, parenting is modeled as static style, behavior, or amount of stimulation. However, parenting is always in part a response to a particular child's proclivities, temperament, personality, and needs, and these results suggest that parents, to some degree, may be attempting to provide the best "fit" for their child between environmental possibilities and what their child's growth and development requires (Sameroff, 1998; Bradley & Corwyn, 1995).

CHAPTER FOUR: Child Characteristics and Successful Use of Housing Vouchers: Estimates from the Moving to Opportunity Demonstration

In my two previous chapters, I examined how children's characteristics influence proximal measures of the environment. In this study, I examine whether children's behaviors or characteristics also influence broader developmental contexts, such as their neighborhood environment, via their influence on parental take-up of housing vouchers.

Housing policy: The context of the study

"A decent home in a suitable living environment for every American family" (Housing Act of 1949) has been a long-standing policy goal in the United States. For much of the 20th century, the federal government worked toward this goal with the construction of project-based housing; more than one million public housing units were built after passage of the Housing Act of 1937 (Schill, 1993). Beginning in the 1970s, however, federal low-income housing efforts began to shift away from project-based assistance and towards voucher-based approaches that allow families to rent in the private market. Today, about 2.1 million low-income families receive housing vouchers supplied by the U.S. Department of Housing and Urban Development's (HUD) Section 8 rental subsidy programs (Center on Budget and Policy Priorities, 2003).

Voucher-based assistance has become a popular alternative to project-based housing for several reasons. First, research has suggested that project-based housing concentrates poverty, which in turn is associated with diminished child well-being, lower adult employment, reduced social efficacy and increased drug use, crime, and violence (Brooks-Gunn & Duncan, 1997; Crane, 1991; Sampson, Morenoff, & Earls, 1999; Wilson, 1986, 1996). Legal and civil rights concerns have also been expressed about the segregating effects of project-based housing (Massey & Denton, 1993; Rubinowitz & Rosenbaum, 2000).

The move away from project-based housing has also been motivated by a desire to stem the escalating costs of project-based programs (Shroder & Reiger, 2000). Analysts have suggested that a market-driven, voucher-based system of housing allocation is more efficient than project-based assistance, with lower overall costs and higher satisfaction for residents.

As the public housing stock ages and deteriorates and maintenance costs mount, it can be cheaper for housing authorities to tear buildings down and provide households with vouchers rather than to renovate existing buildings. Olsen (2001) suggests that these tenant-based vouchers provide equal- or better-quality housing at a much lower cost than any type of project-based assistance. For these reasons, by the late 1990s, the voucher-based approach became one of the two main components of HUD's housing policy strategy, the other being the creation of mixed-income communities (Popkin, 2000). Federal budget allocations reflect this change in strategy as well, with an estimated $14.8 billion spent on tenant-based assistance and $5.3 billion on project-based assistance in FY 2005 (Office of Management and Budget, 2005).

With the emphasis on vouchers as the vehicle to provide low-income housing comes an implicit assumption that families will be able to successfully use the voucher to lease a residence in the private market, a concept called "take-up." Successful take-up of vouchers is far from universal, however. Finkel and Buron (2001) estimate that only 69 percent of families offered a Section 8 voucher in 2000 succeeded in using them to move to a new residence, compared with 80 percent in the late 1980s. Low take-up rates are a concern because they lead to lower efficiency, higher costs, and fewer families being able to enjoy program benefits (Currie, 2004). In the case of Section 8 vouchers, the voucher is unlikely to be wasted, because if the voucher is unused it will be re-assigned to another family on the waiting list. However, this still results in higher overall administrative program costs.

More importantly, however, low take-up rates are worrisome for another reason: as low-income housing policy increasingly moves towards tenant-based allocation, households that are unable to make use of vouchers may suffer from inadequate housing. For example, if households with young children are systematically less likely to take-up vouchers, these types of households may be disadvantaged in their long-term housing and neighborhood outcomes. Qualitative work (Popkin, Cunningham, & Burt, 2005; Popkin & Cunningham, 2002) has suggested that there is indeed a substantial proportion of residents or families in public housing who are "hard to house" owing to drug, alcohol, and mental health problems, disabilities, criminal records, or large household size. They estimate that between one- and two-thirds of current HOPE VI residents face serious obstacles in navigating the housing voucher program, the private market, and maintaining a stable housing unit. Better understanding of which households are less likely to successfully lease up can help tenant-based housing policies and programs to better target populations at risk for lease-up failure as well as aid our understanding of the need for an increased supply of particular types of affordable housing units appropriate for these household types, such as assisted housing for families with members who are disabled.

Although a number of studies have examined how various characteristics of adult housing voucher recipients relate to take-up, many questions remain as to why some households successfully take-up vouchers and others do not (Currie, 2004). Despite the fact that the majority of households that use vouchers also have children (HUD User 2000), few studies have examined the influence of children's characteristics on take-up. We do know that children can have quite profound influences on parents' behavior, choices, opportunities, employment, and overall life course (Bell, 1968; Thomas & Chess, 1968; Crockenberg & Leerkes, 2001; Reuter & Conger, 1998). This study examines whether characteristics of children – including school history, health, and behavior – can also influence the probability that their family will take-up a housing voucher.

Background

Housing mobility programs

This paper uses data collected from the Moving to Opportunity demonstration program to estimate the influence of child characteristics on a household's probability of Section 8 housing voucher take-up. The MTO demonstration was a random assignment housing mobility program designed to test the effects of neighborhood placement on family well-being. The demonstration was conducted between 1994 and 1998 in five cities: Baltimore, Boston, Chicago, Los Angeles, and New York. The target population was very low-income families with children living in public and assisted housing projects located in high poverty census tracts. Applicants who passed a screening test and credit check were randomly assigned to one of three groups. Families in the experimental group (N=1,729 families) received counseling to help them with moving as well as a housing voucher that could only be used in areas where less than 10 percent of households were below the poverty line. Families in the Section 8 group (N=1,209 families) received a standard Section 8 voucher, which can be used to rent any apartment, regardless of location, that meets rent specifications and passes housing inspections. Families in the control group (N=1,310 families) did not receive a housing voucher but continued to be eligible for other assistance. The MTO interim evaluation (Orr et al., 2003) found large impacts on treatment families' neighborhood location, neighborhood quality, and maternal psychological health. There were few to no effects on maternal work and child academic achievement. Effects on child behavior were mixed, with positive effects for adolescent girls and negative effects for adolescent boys.

The motivation behind the MTO demonstration came from the Gautreaux Program, a federal court-ordered racial desegregation program in Chicago. Participating families were helped to move out of racially isolated areas through the (then new) tenant-based Section 8 program; encouraging outcomes were found for many Gautreaux families. In 2001, as a result of ongoing litigation, the Chicago Housing Authority (CHA) contracted with the Leadership Council for Metropolitan Open Communities to implement a new round of the Gautreaux residential mobility program. Residents who were current lease-holders in good standing in CHA public housing were eligible to sign up for a Housing Choice Voucher (HCV) through the Gautreaux Two program. Take-up was quite low for "Gautreaux 2" (Pashup et al., 2006).

Factors influencing take-up

In exploring questions of social program take-up, economists have developed utility-maximizing decision models that assume take-up is the result of participants weighing the payoffs of participation in the program against the costs of participation in the program (Moffitt, 1983; Currie, 2004). When modeling take-up among housing program participants, for instance, whether a family takes up a voucher or not would be seen as the result of the family weighing the costs and benefits of finding and moving to a new unit against the costs and benefits of staying in their current location (Kennedy & Finkel, 1994; Shroder, 2002). To the extent that families have incomplete information about these costs and benefits in order to make the decision, this can also be included in the model.

A growing literature on factors related to housing voucher take-up has identified several promoters and barriers to a family's successful move. First, factors beyond the control of households, such as landlords, rental markets, racial discrimination, and explicit program design characteristics are important determinants of take-up. Landlord preferences for particular types of families can affect take-up rates. A landlord's familiarity with the housing voucher program can influence his willingness to lease to program participants; research suggests that renting from a landlord who has had prior experience leasing to Section 8 families increases the chance of successful take-up (Kennedy & Finkel, 1994). The tightness of the local rental market is also a key factor. Finkel and Buron (2001) found that take-up rates in very loose markets are 20 percentage points higher than in the very tightest markets, and Shroder (2002) also found a significant effect of metro area vacancy rate on take-up.

Qualitative studies suggest that voucher holders see a lack of rental units as a major obstacle to mobility (Pashup et al., 2006). Racial barriers and discrimination are also an important factor influencing take-up rates (Pashup et al., 2006; Rubinowitz & Rosenbaum, 2001; Bobo & Zubrinsky, 1996; Crowder, 2001; DeLuca & Rosenbaum, 2003; Logan, Alba, & Leung, 1996; Pendall, 2000). Finally, programmatic restrictions on where families can move, as were used in the Gautreaux and Moving to Opportunity (MTO) programs, appear to have a particularly strong effect. In the Moving to Opportunity program, for example, the experimental group was required to use their housing vouchers in neighborhoods where less than 10 percent of households had incomes below the poverty line, whereas the Section 8 group faced no neighborhood restrictions. Shroder (2002) estimated that this restriction on placement neighborhood decreased the probability of take-up by at least 14 percentage points among the experimental group.

Successful lease-up also varies with participant characteristics. Qualitative research from the Gautreaux II project suggests, for example, that moving is less likely among those who work (Reed, Pashup, & Snell 2005). Shroder's (2002) analysis of the Moving to Opportunity did not find work effects, but was based on a sample from 1997. (The Gautreaux II finding was based on a sample from 2003, and differences in results between the two studies may be due to increasing opportunity costs of nonwork related to welfare reforms such as the loss of entitlement programs, increased sanctions, and the rise of welfare-to-work programs.) The availability of transportation also affects costs associated with searching and moving. Several studies have found that participants fare better when they have reliable access to transportation, particularly automobiles (Shroder, 2002; Pashup et al., 2006), during their search, perhaps because this reduces the time spent house-hunting and increases their geographic reach beyond transit-accessible neighborhoods.

Other personal characteristics of the head of household, such as age, work status and disability, may also influence take-up rates (Shroder, 2002; Pashup, et al. 2006). Finkel & Buron (2001) found that older householders are less likely to successfully lease up with a housing voucher. Households with members who have problems with substance abuse, mental health, or domestic violence also experience lower success rates (Popkin et al., 2002).

Studies of other social programs have suggested that family size can influence program take-up. Family size is positively correlated with successful program take-up of Medicaid (Currie 2004), perhaps because larger families benefit more while facing a similar cost of enrollment. The opposite has been found for housing vouchers: larger families are less likely to successfully lease up owing to the difficulty in finding large rental units (Finkel & Buron, 2001; Popkin, 2002; Shroder, 2002; Pashup et al., 2006).

Psychological variables, including motivation to leave the old apartment and neighborhood and relocate to a new apartment or neighborhood, also relate to take-up. Not surprisingly, participants who express greater interest and motivation for moving are more likely to lease up successfully, while higher social connectedness in the baseline neighborhood and uncertainty about liking a new neighborhood can decrease the probability of moving (Shroder, 2002). Research suggests that apprehension about the racial and cultural constitution of new neighborhoods also may have a negative impact on lease-up rates (Pashup et al., 2006; Rubinowitz & Rosenbaum, 2000; Shroder, 2002).

Qualitative evidence suggests that housing search skills, including understanding program requirements and how to find a unit, as well as the quantity and quality of available housing market information, can act as promoters or barriers to participants' lease-up success (Pashup et al., 2006). Housing-search assistance can help families with lower search skills negotiate the search and moving process (Cunningham & Popkin, 2002; Shroder, 2002), but the quality and type of assistance matter (Feins, McInnis, & Popkin, 1997).

Currently, however, we know little about how child characteristics might positively or negatively influence a family's ability to move. Shroder's (2002) study of the Moving to Opportunity experiment examined the influence of only three variables – number of school-age children in the household, number of pre-school-age children in the household, and householder comfort with their children moving to a nearly all white school – on take-up of a standard Section 8 voucher (the Section 8 group) and on take-up of a voucher restricted to low-poverty areas (the experimental group). The number of school-age children in the household had no effect on lease-up among the experimental group or among the Section 8 group. Shroder did find, however, that the number of pre-school-age children in the household significantly raised the probability of lease-up in the Section 8 group, but not in the experimental group. A psychological variable measuring the level of comfort with having one's children in a nearly all-white school was a statistically significant predictor of success among the experimental group, but not among the Section 8 group.

Neither the Shroder study, nor any other of which I am aware, examines how child characteristics such as health, behavior, or academic problems relate to probability of lease-up. Since many of the families either receiving or eligible for vouchers have children, it is important to understand whether child characteristics affect a family's ability to make use of mobility programs,

The influence of child characteristics on take-up

How might child characteristics, such as children's age, behavioral problems, academic experiences, or health status influence take-up? First, parents may be more likely to move if they wish to remove a misbehaving teenager from the temptations of a dangerous neighborhood. Parents report trying to regulate their children's behavior by managing the initiation and regulation of their children's peer contacts (Parke, 2004, Furstenberg, et al., 1999, Mounts, 2000) and acting as environmental "gate-keepers" (Parke et al., 1994; Cooper & Cooper, 1992; Furstenberg et al., 1999). For example, about one-half of the parents in a Philadelphia study (Furstenberg et al., 1999) tried to keep their adolescents at home and out of the neighborhood and a smaller portion of parents would allow their adolescents to do activities, but only outside the home neighborhood. Notably, none of the families in the Philadelphia study was able to move as a strategy to manage their children's environments, although the authors' note that this strategy was frequently mentioned as a potential tactic by many parents.

The Philadelphia study (Furstenberg et al., 1999) suggests that urban parents make large efforts to manage, and even change, their adolescents' daily environments. However, the study does not examine whether parents make *more* of an effort to manage their children's environments if their adolescents have specific problems, such as running with the wrong crowd or doing poorly in school. Only one study has examined whether parents who have children with problems might be more likely to take-up housing vouchers. In a study using early results from the Moving to Opportunity, Ludwig, Duncan and Hirschfeld (2000) found that voucher take-up was higher among households that had adolescent members with criminal records. These results suggest that parents might respond to their child's bad behavior with increased motivation to move the child and family to a better environment.

On the other hand, many other studies suggest that children's problems, such as poor health or behavioral problems, might make it *less* likely for a parent to move. For example, children's health problems often increase maternal stress and depression and decrease maternal efficacy (Crockenberg & Leerkes, 2001). Parents with disabled children have lower rates of employment, lower income levels, and more mental and physical health problems than the general population (Seltzer et al., 2001; Hauser-Cram et al., 2001). Families that have children with health problems tend to have fewer emotional and financial resources, and this might limit their ability to effectively search for housing and to take the necessary and numerous steps needed to effectively lease up. In addition, there is good evidence that households that have adult members with mental health, substance abuse, or other types of disabilities face lower rates of take-up (Shroder, 2002; Popkin et al., 2002). Perhaps households that have child members with disabilities might face similar obstacles. Families with multiple problems often experience the most distress (Sameroff et al., 1998).

In summary, there is only one published study that suggests child problems might increase the probability of take-up and a number of studies that suggest the opposite. Thus, I hypothesize that child problems will reduce take-up. A child's health or behavioral problem might make it more costly for her parent to successfully take-up a voucher, because the child's disorder, illness, or disability decreases the monetary and/or psychological resources for attending informational sessions, meeting with counselors, looking for a new apartment, and moving. Moving may also carry fewer benefits for the household that has a child with behavioral or health problems because the child may have long-standing relationships with doctors or counselors in the home neighborhood which a parent may be loathe to disrupt.

I also predict that the cumulative impact of multiple child health or behavioral problems may have particularly negative impacts on take-up. I predict that the influence of children's problems should be stronger for households receiving standard Section 8 vouchers compared with households that receive a voucher only good in low poverty neighborhoods along with the substantial counseling assistance to help them use the voucher (the Experimental group). The counseling intervention included services such as transportation assistance, referrals for mental health and health care, and assistance in obtaining child care (Feins, McInnis, & Popkin, 1997). All of these could have been of use to families with children who have health, behavioral, or educational problems. This counseling, I hypothesize, might then compensate for the limitations a family that has children with problems would normally face in their housing search. Thus, I predict that the effect of children problems will be greater for the Section 8 group than the Experimental group.

Finally, I predict that households with higher human capital will be more likely to move when one of the children in the household has been identified as gifted or been identified as having health or behavioral problem. I predict that this might be the case because parents with higher human capital would be more likely to seek out neighborhoods with the resources to nurture their child's talents or address their child's difficulties.

Analytic approach: Using the MTO experiment to model take-up

At the time of enrollment, just prior to randomization, the head of household completed a baseline survey, answering questions about herself (most respondents were female) and other household members, including each child in the household under age 18 years. Abt Associates conducted random assignment, baseline data collection, and the five-year data collection.

The sample is comprised of the 2,938 MTO families who were randomly assigned through December 31, 1997 to the experimental and Section 8 groups (out of a total of 4,248 families in the MTO demonstration through that date).[3] I do not include the 1,310 families in the control group because my question of interest concerns take-up of the housing voucher, which only applied to the Section 8 and experimental groups. All independent and control variables come from the baseline survey answered by each head

[3] This is not the entire MTO population: intake continued in one site (Los Angeles) through July 1998, and lease-ups occurred there until March 1999. The full MTO sample included 4,608 families.

of household. The outcome variable – whether the household successfully moved and leased up in a new residence – comes from administrative data. To prevent the loss of cases, missing values are recoded to "0", and dummy indicators are included in the analyses to adjust for these cases. My final sample is comprised of the heads of 2,938 households and the 7,348 children in those households, including biological, adopted, foster, and grandchildren.

The paper builds on previous work by Shroder (2002), who examined how baseline adult characteristics, as well as information on the strength of the local housing market and quality of the counseling services received by the experimental group, related to successful lease-up in the MTO experiment. I extend the analysis of MTO data to estimate the relationship between the characteristics of the children in the household at baseline and the probability that families will take-up a housing voucher. Child characteristics are represented by dummies for whether any child in a family has a particular attribute.[4]

A dummy variable indicating program take-up of the housing voucher was used as the outcome variable in logistic analyses. These analyses allow us to estimate the association between the characteristics of children in a household and a household's probability of lease-up. The logistic coefficients generated from the models are used to estimate the change from the baseline take-up probability of 52.2 percent for the sample overall. Owing to the large number of independent variables in my models, I tested for multicollinearity by comparing the size of the standard errors in full models to the standard

[4] I ran two additional analyses, one at the child level, where we estimated the association between any one child's characteristics and his or her family's chance of take-up, and another at the household level, where we estimated the association between the proportion of children in the household with a particular characteristic and take-up. The results from these analyses are quite similar to the results of the analytic approach discussed here and are available upon request.

errors of reduced-form models. Standard errors were of similar magnitude in both full and reduced-form models, indicating that multicollinearity was not a problem.

After examining the main effects of child characteristics on the household's probability of take-up, I explore whether the effects of child problems and child talent vary as a function of group assignment (Experimental versus Section 8) and householder human capital. This was done by independently entering a series of interaction terms into the regression, including interactions between child problems (or gifted status) and the potential moderator of group assignment or householder human capital. I used the Norton, Wang, and Ai (2004) algorithm for computing interaction effects and their standard errors in logistic regression.

Measures

Outcome measure

My outcome of interest is whether a household took-up their housing voucher and moved through the program. The measure is a dummy indicator with "1" indicating the household took-up their housing voucher and "0" if the household did not take-up the housing voucher. Just over half of all households took up the voucher (Table 4.1).

Child characteristics measures

My key independent variables of interest are measures of child characteristics gleaned from the baseline interview. Dummy variables indicate whether any child in the household had a given demographic characteristic as well as indicators of child health, behavior, and school problems (Table 4.1).

I include measures indicating whether the household had any children aged 0-5, aged 6-12, or aged 13-17, male children, and whether there was any child in the household not a natural-born child of the respondent. I include measures of whether any child in the household had a physical, emotional, or mental problem that: necessitated him needing special medicine or equipment; made it hard for him to get to childcare, pre-school, or school; made it hard for her to play active games or sports. An important feature of the baseline survey completed for each child in the household was that although there were some questions asked about all children in the household, some were only asked of children aged zero to five years and others asked only of children aged six to seventeen years. I include two health-related variables about children under the age of six: whether any child in the household was: of low-birth weight, or under six pounds at birth and in the hospital prior to his first birthday due to sickness or injury. I include responses to four health, school, and behavioral questions about children between the ages of six and seventeen: whether any child in the household: was attending school; got special help in school or had gone to a special class for behavioral or emotional problems in the two years prior to baseline; had received a call from school concerning problems with schoolwork or behavior in the two years prior to baseline; had been expelled or suspended in the two years prior to baseline; and was currently in a gifted class or did advanced work in any subject.

To test my hypothesis that an increasing number of child health, academic, or behavior problems might relate to greater difficulty of the take-up of housing vouchers, I created a cumulative household problem index that reflected the total number of child educational, health, and behavioral problems that existed in the household. About two-fifths of households had no child problems while 12 percent had four or more. In addition, I created measures to examine whether there were non-linear associations between child problems and take-up by creating indicators for each child problem level, as well as an indicator that a household had two or more child problems. Thirty-seven percent of households had two or more child problems.

Household control measures

I group the baseline control measures hypothesized to be related to successful lease-up into several different categories, including demographic characteristics, psychological and motivational attitudes about moving, social network size, householder assessment of neighborhood (as defined by the respondent) safety and quality, householder assessment of housing safety and quality, householder employment and welfare receipt characteristics. These measures all come from the baseline survey answered by the head of household prior to random assignment. Means and standard deviations for family control variables are summarized in Appendix Table 1.

Demographic measures

Baseline demographic measures consist of dummy variables for: the householder's experimental group status, program site, age category, race, and Hispanic ethnicity. I include continuous measures of the total number of residents in the household, the number of children aged 0-5 years, and the number of children aged 6-17 years.

Socioeconomic status and background measures consist of dummy variables for whether the householder: has a high school diploma, has a car, has a license, has never been married, ever received AFDC, had previously applied for a Section 8 voucher, had moved more than three times in the last five years, was a parent before age 18, lived with both parents at age sixteen, and lived in a family that ever received food stamps. I created a measure of “high” human capital that took into account whether the householder finished high school, lived with both parents until age 16, had not become a parent until age 18, and was not currently receiving AFDC. Those respondents who had three or four out of these four characteristics were considered to have “high” human capital as compared with the rest of the sample. Twenty-five percent of respondents were in this category.

To measure respondents’ neighborhood histories, I include continuous measures of how long they had lived in their neighborhood and how long they had lived in their apartment, as well as dummy indicators for prior neighborhood racial and ethnic composition.

Baseline motivation about moving

The MTO baseline questionnaire also asked psychological and motivational questions about the respondent’s potential move. I use dummy variables indicating to which type of neighborhood – the same neighborhood, somewhere else in the city, a suburb, another city, or other – the respondent wanted to move. I also created an index that measured how the respondent felt about moving. This index is an average of the following standardized variables: whether the respondent wanted to move, how positive she felt about moving, how confident she felt about finding a new apartment, how sure she felt that she would like to live in a new apartment, how sure she felt that she would like to live in a new neighborhood, how sure she felt that she would get along with her new neighbors, how sure she felt that she would like living in a neighborhood where the majority of her neighbors make more money, how sure she felt that she would like living in a neighborhood where all her neighbors make more money, how sure she felt that she would like living in a neighborhood with neighbors who earn more than she does, how sure she felt that she would be able to get a job in their new neighborhood, how comfortable she would be with her child attending an all white school, how comfortable she would be with her child attending a school where half the children were white, and how sure she felt that she would be able to keep her child out of trouble in the new neighborhood. The Cronbach alpha (a reliability measure of how well a set of variables measures a single latent construct) for this measure is 0.77. Finally, I include measures of the reasons why the respondent was interested in moving, with dummy indicators indicating whether a particular reason was the first or second reason they would like to move. These reasons included getting away from gangs and drugs, a bigger and better apartment, better schools, finding a job, and moving closer to current employment, and a category for other reasons.

Baseline friends and networks

As the strength of a respondent's neighborhood, friend, and family social networks might have an effect on her probability of moving, I developed an index of the respondent's social network. This index was an average of the following measures (all measures were standardized): how many of her friends live in her current neighborhood, how many of her family members live in her current neighborhood, how often she lends items to neighbors, how often she borrows items from neighbors, how often she watches a neighbor's kids, how often she eats with a neighbor, how often she stops to chat with a neighbor, how likely it is that she would tell a family in the neighborhood that their child is getting in trouble, and how likely it is that another parent would tell her that her own child is getting in trouble. The Cronbach alpha for this measure is 0.70.

A measure of parental school involvement was created by averaging four items pertaining to school involvement: whether the parent or another adult who lives in the household had gone to a general meeting at school, had gone to a school or class event like a play, sports event, or science fair, had volunteered at school, or had worked with a youth group, sports team, or club outside of school. The Cronbach alpha for this measure is 0.85.

Baseline neighborhood safety and quality

An index of neighborhood safety and quality was created using variables measuring the respondent's feeling about her baseline neighborhood's quality and safety. This index is an average of the following standardized variables: overall respondent satisfaction with baseline neighborhood; problems in the baseline neighborhood with litter, graffiti, public drinking, drugs, and abandoned buildings problems; how safe the respondent feels in the parking lots and sidewalks near school, at home alone at night, in the streets during the day, and in the streets at night; and whether in the last 6 months someone in the household had a purse snatched, was threatened with a knife or gun, was beaten or assaulted, was stabbed or shot, or experienced a break-in. The Cronbach alpha for this measure is 0.81.

Baseline apartment characteristics and condition

I created an index of baseline apartment conditions by averaging the following standardized items: the overall condition of the baseline apartment and the extent of problems with peeling paint or broken plaster, rats or mice, locks, windows, plumbing system, heating system, stove or refrigerator, wire or electrical problems, or problems with too little space. The Cronbach alpha for this measure is 0.80.

Baseline work and assistance

The respondent's work and assistance status was measured with dummy variables indicating whether the respondent was: working at baseline, looking for work, attending school, and did small jobs, or receiving food stamps, Supplemental security income, social security, child support, educational assistance, unemployment, Medicaid, WIC, or AFDC receipt.

Results

Table 4.2 presents the logistic regression results of program take-up regressed on the household's children's characteristics and controls. I display only the results for the children's characteristics, as these are the variables of interest for this analysis, although I discuss variables that reach statistical significance from the full model (full regression results are presented in Appendix Table 2).

Households with a child with an emotional, behavioral, or medical problem that made it hard for them to go to school experience a 12 percentage point decline in probability of take-up[4] (from 52 percent to 40 percent) and households that had a child aged 0-5 years who were of low birth-weight experience a 10 percentage point decline in probability of take-up (from 52 percent to 42 percent). None of the other problem indicators were statistically significant predictors of take-up.

[4] The new probability of take-up is calculated with the following formula: $.522^* e^{\text{logit coefficient}} / .522 + .522^* e^{\text{logit coefficient}}$

I fail to find any association between basic child demographics and take-up: whether a household had a child of particular age (whether having two or more young children, or three or more older children) or gender, or whether the household has a child that is not a birth child, had no bearing on the household's take-up of a housing voucher. In addition, I fail to find any association between take-up and whether a household has a gifted child.

Cumulative risk framework

I also hypothesized that the cumulative effect of child problems might in fact influence whether a family can take-up a voucher or not. In Table 4.3 I present results from this cumulative risk framework. I find that for every additional problem in the household, the probability of moving declines by 3.6 percentage points.

I wished to understand whether the cumulative problem index had non-linear associations with take-up, so I also ran regressions including indicator variables for various levels for child problems, with having no problems being the omitted group (Table 4.3). These models included the full battery of independent variables used in the prior analysis. The coefficient on "one problem" is essentially zero, but the coefficients on all the dummy indicators for two, three, four, five, and six problems are in the negative direction, although only the coefficient for two problems and six or more problems reach standard levels of statistical significance. When I test constraining all the coefficients on the variables of for two, three, four, five, and six or more problems to be equal, my results indicate that I cannot reject the hypothesis that all of these coefficients are identical. This suggests that the preferred model compares households with two or more and fewer than two problems.

When I ran a regression including a variable indicating that the household has two or more child problems (again, including the full battery of controls), I find that this is associated with a 7 percentage point decline in the probability of moving compared with those who have none or only one child problem (Table 4.3). The three models – the linear model, the dummy indicator model, and the two problem or more versus less than two problem model – all had approximately the same fit (with an adjusted R^2 of .11), so it is not clear that one model better explains the association between child problems and take-up better than another. Overall, these results suggest that households that have more than one "child problem" do face increased difficulty with a successful lease-up with a housing vouchers.

Do impacts vary by group assignment or human capital?

I hypothesized that child problems, or child gifted status, might have a different bearing on take-up depending on group assignment, so I tested whether there were interactions between child problems or child gifted status and random assignment status (as Experimental or Section 8). I failed to find any statistically significant interactions between group status and child problems (measured as individual variables or as the cumulative risk variable). I should note, however, that although the interactions were not significant at the standard level, the general trend was that child problems were more highly associated with decreased take-up for the Section 8 group. I also ran regressions examining whether child gifted status and/or child problems interacted with householder human capital, but found no evidence of any interaction. Results from all interaction analyses are not presented here but are available by request.

Results from full model

My findings from the full model are similar to the other quantitative analysis of take-up in the MTO study (Shroder, 2002). Living in Baltimore or Los Angeles, compared with New York, Chicago or Boston, was associated with higher rates of take-up. Being a younger respondent (aged 20-29) was associated with higher rates of take-up compared with those aged 30-39. Being an older respondent (40+) was associated with lower rates of take-up compared with those aged 30-39. Those who had previously applied for Section 8, felt positively about moving, had weaker neighborhood social networks, and who rated their neighborhood poorly were more likely to successfully move. I found no significant effects from householder racial status, education level, marital status, or car ownership.

Discussion

My results suggest that basic child characteristics have little bearing on the take-up of housing vouchers. They indicate that families with young children or families with teenagers, for example, will not face extra difficulty using their housing vouchers.

I did find, however, that child health, behavioral, or educational problems that make it difficult for the child to go to school as well as the presence of a low birth-weight child pose a hindrance to families trying to move through housing voucher programs. Perhaps moving is less attractive because the special educational or medical services these children may require to get to school and/or attend class would have to be rearranged. In addition, if the child had a physical disability that made it difficult for him to go to school, this could very well mean the child would require a handicapped-accessible housing unit. In a similar way, the presence of a low birth-weight child – who would be at an increased risk for a host of medical problems – could make moving difficult for a family. I note, however, that giving birth to a low birth-weight baby is more common among sicker, younger and poorer women. To the extent that a woman's health, age, or socioeconomic status are not being captured by the numerous controls, the association between low birth-weight and decreased take-up may be correlative rather than causal.

To put these effects in context, the size of the coefficients for these two child problems were a little smaller than the programmatic effect of being in the Experimental group or a one standard deviation change in baseline feeling about moving and a little bigger than a one standard deviation change in baseline neighborhood satisfaction and network strength.

In addition, I found that families with any two "child problems" were less likely to move through housing vouchers. (I examined whether this was because these families were more likely to have one of the two problems – low birth weight and difficulty going to school – that individually predicted take-up, but did not find this to be the case.) Presumably, multiple problems reduce successful take-up due to a combination of increased "costs" and decreased "benefits": negotiating the private market and finding units that are appropriate for their children's physical needs may be more difficult for these families, while moving may mean the disruption of a network of social, educational, or medical services.

These results are concerning, as about eight percent of American children have been identified as having a learning disability, while about two percent suffer from fair or poor health, and about eight percent were of low weight at birth (Bloom & Dey, 2006).

Among low-income children, rates of physical, behavioral and academic disability are even higher than in the general population: about one in six low-income children, for example, are born with low birth-weight (Martin et al., 2003), and in my sample, about one-half of all households had at least two children with problems or one child with at least two problems. This high prevalence of child problems means that a significant portion of the families to whom housing vouchers are targeted may be at risk for lower take-up rates due to the presence in the household of a child or children with disabilities.

My finding that there are not significant differences between Section 8 and experimental groups means that the effect of child characteristics on take-up was not reduced in the Experimental group, which did receive assistance with their move. One might hope that the effect of child characteristics would be less harmful for the experimental group due to the additional counseling assistance they received, but recall that this group also had a more arduous process to find a home and move due to the restriction in neighborhoods in which they were allowed to move to. In fact, it is possible that the counseling services may have helped families of children with problems to move, but that the greater difficulty in finding housing to move to canceled out any positive benefits. Further research is needed on whether counseling is helpful to “hard to house” families due to children with disabilities or other problems. I also failed to find evidence of an interaction between householder human capital and child problems or gifted status. Most families in this sample were very poor and disadvantaged, so perhaps the range of human capital was not large enough to pick up an interactive effect.

While the MTO research platform may be the best I have to date for examining these issues, there are limitations in using this study. In particular, participation in MTO was limited to residents of distressed public housing, who are likely quite different from the general voucher population who come off housing authority waiting lists. The extent to which my findings would translate to this population is hard to say. In addition, ten years has passed since the sample was drawn for this study, and it is quite likely that the population currently eligible for vouchers is different than it was ten years ago. I can speculate that the population might be even more at-risk today than it was a decade ago, but further research is needed to help us understand the processes by which child characteristics influence take-up. In particular, open-ended qualitative interviews can help us better understand what households with children who have problems find most challenging in their search.

My findings that child problems are associated with decreased take-up add to the already existing literature linking adult mental health and physical health problems with difficulty taking-up housing vouchers and other social programs. This study, along with the wider literature (Popkin, Cunningham, & Burt, 2005), suggests that unless policy makers and program implementers find ways to effectively target those families with problems, programs will continue to suffer reduced take-up among this particularly needy population.

Funding for Section 8 has been diminishing with the current policy climate. To the extent that families are competing for increasingly scarce voucher resources, it is arguably important to know whether or not families are competing on equal footing. Echoing

Popkin's findings, this study suggests that this is not the case for families with children who have multiple physical, emotional, and behavioral problems. Policy makers, program staff, and housing researchers should consider programs or techniques that might best address these families' needs. Perhaps, as Popkin argues, housing all families through vouchers should not be the aim and instead better supportive housing be provided to those families most "hard to house." Alternatively, programs could provide better screening and counseling services for families with children with problems. Such households may need assistance in finding accessible units, identifying new medical facilities or obtaining transportation to care. Further research is necessary to determine how to best meet these families' needs for housing.

American families who have children with health, emotional, or educational disabilities bear most of the burden of their child's disability. Surely it is not this group of families that the American public or policy makers would want to fall through gaps in the safety net. It may take more effort on the part of policymakers or program implementers to serve these families, but we must adequately provide for these households that do so much for their children, such that they too can enjoy a "decent home in a suitable living environment."

This study suggests that children's characteristics can influence their developmental contexts through parental moving decisions; this is an evocative process. Parents appear to respond to their children's characteristics with increased or decreased motivation, desire, or ability to take advantage of housing vouchers and moving the child and family to a different neighborhood. The evocative process affects not just micocontexts, but also children's broader, neighborhood contexts as well.

CHAPTER FIVE: CONCLUSION

Human development theory emphasizes the role culture, policies, neighborhood, and parents play in shaping children's developmental contexts and environments, but much less attention has been paid to the role children themselves play in influencing environments via evocative effects. The work in this dissertation, building on a nascent literature, demonstrates that children do play an important role in influencing their own environments through their evocative effects on adults. The theoretical framework for the dissertation derives from the Bronfenbrenner tradition of human ecology, as well as other human developmental theories that emphasize the importance of interaction between the child and the environment in shaping development. In the interest of extending this literature, my three studies examined the evocative effects of children's characteristics that are infrequently studied, using multiple methodological techniques to model and examine the evocative response. I also examined the evocative response across various ages of children, characteristics of families, and contexts of development.

In the first essay, I examined the evocative effect of children's language and cognitive development on their language stimulation environments using OLS, OLS-lagged dependent variable, and change models. Results suggested that young children's cognitive-linguistic development influence the quality of care they receive in child care, with quality defined as language stimulation. Results also suggest that these evocative effects were stronger for toddlers (aged 15 and 24 months) compared to older children, for whom results were mixed. However, the evocative response did not vary by child care context (center care versus non-center care).

In the second essay, I examined the evocative effect of children's language and cognitive development on their home learning environment. Using multiple analytic techniques, including OLS, fixed effect, and multilevel modeling, I found that children with more advanced cognitive capabilities evoked higher quality home learning environments. Evidence was mixed that this effect varied by child age, gender, or family socioeconomic status.

In the third essay, I examined the effect of children's characteristics on parental moving behavior. My results suggest that basic child characteristics have little bearing on the take-up of housing vouchers. They indicate that families with young children or families with teenagers, for example, will not face extra difficulty using their housing vouchers. I did find, however, that child health, behavioral, or educational problems that make it difficult for the child to go to school as well as the presence of a low birth-weight child pose a hindrance to families trying to move through housing voucher programs. Families with children with multiple problems were much less likely to move than those with no or only one problem.

These results carry important implications for human development theory, methodology, and policy and practice.

Theoretical considerations of evocative effects

Transactional theories of development are central to the field of human development. Yet these theories have little to say about what type of child characteristics matter for evocative effects, or how important they are. They are also generally silent on whether evocative effects matter more or less at various points in development or in different contexts.

Past work in this area has tended to focus on children's temperament or behavioral characteristics, and this dissertation provides new evidence that child language and cognitive characteristics can influence measures of child care quality, as well as the quality of the home learning environment. Past research suggests that cognitive growth is particularly dependent on exposure to the environmental stimuli that is neither too easy nor too difficult – the "zone of proximal development" (Vygotsky, 1962; Rogoff & Wertsch, 1984). This suggests that children may evoke the learning and language environment that best fits their current developmental and learning needs, and that evocative effects may be a key process by which children produce person-context fit (Lerner, 1983).

My dissertation also attempted to contribute to theories of bidirectionality by examining how child age might moderate evocative effects as children develop, as well as how evocative processes may be moderated by developmental contexts or other child characteristics. It remains unclear, however, the extent to which child age moderates the evocative effect. In Chapter 2, I found some evidence that the evocative effect was stronger at 15 and 24 months when modeled with the lagged-OLS and change approach compared to 36 or 54 months. However, there were few age differences in the evocative effect in Chapter 3, which examined the evocative effect on the home learning environment.

All three essays failed to find differences in the importance of child effects by types of family, program, or child care contexts. Perhaps the process of evocation is a powerful enough effect that it not strongly moderated by contextual parameters. It remains possible, however, that differential evocative effects exist by child age and context, but that demonstrating them requires more precise measures, more sophisticated models, larger sample sizes, and/or more points of measurement. More research is needed to answer this question.

How important are evocative effects? My results suggest that they may be quite important in shaping children's developmental contexts. Although the size of effects are small, the timing of the evocative response is probably not accurately captured in these studies, as none of the original studies were designed to study evocative effects. This suggests that my estimates could grossly underestimate how large and important evocative effects actually are. Yet, even given the fairly small-sized coefficients across my results, the cumulative influence of such evocative effects could be very important over the course of childhood.

This work can also contribute to theory and research in behavioral genetics. Evocative effects may be key processes linking interactions between each level of functioning, from the gene, to the child, to a child's developmental context (Gottlieb, 1991). For example, evocative effects from children's language and/or cognitive proclivities may play a key role in shaping differences in siblings' environments, thus explaining the importance of "non-shared" environment in studies examining the relative importance of the shared "family" environment, non-shared environment, and genetics in shaping children's behavior. The non-shared environment is often found to be as important as the shared family environment in behavioral genetic studies (Rutter, et al., 1997), and evocative processes may be very important in understanding how these non-shared environments operate to influence development.

Methodological considerations of evocative effects

The results also carry important methodological considerations. First, they suggest that analyses of contextual effects on development that do *not* control for the role children play in shaping the environment may be biased. We can really only determine the "effect" of being exposed to language stimulation or a stimulating home environment by taking into account children's baseline proclivities in these areas in the first place, or by using an experiment. .

Thus, researchers should control for child characteristics that might be shaping developmental contexts. These results underscore the importance of being thoughtful when designing longitudinal studies of development in context; in order to assess and keep track of transactional processes, studies must be designed to do so (Willet, Singer, & Martin, 1998; Duncan, Magnuson, & Ludwig, 2004). These results also suggest that factors often considered static and exogenous to the child must be modeled as endogenous, dynamic, and relational, such as the quality of the home environment, and extending this, school settings as well. Classroom settings, of course, are also under the influence of other children's evocative effects, which greatly adds to the complexity of the analysis.

The results also suggest that evocative effects are an important process to study in their own right. That said, it can be difficult to model and study evocative effects. Empirical research on interactional effects are infrequent in the empirical literature because there are few testable models and because of methodological limitations in separating cause and effect (Pulkkinen and Caspi, 2002). Evocative effects can be especially difficult to model when they are time-varying predictors, as was the case for my first and second empirical studies. In addition, child cognitive and language development are reciprocally associated with my contextual outcomes of interest. Such ambiguity in the temporal ordering of predictor and outcome is a central threat to internal validity (Shadish, Cook, & Campbell, 2002). Willett and Singer (1998) argue that "internal" time-varying predictors, that describe an individual's potentially changeable status over time, are the most problematic of time-varying attributes to model. The more "control" a study participant has over his or her predictor values, the more tangled the modeling will be. Singer and Willett (2003) recommend using prior measures of the independent variable of interest to diminish the possibility that findings are clouded by reciprocal causation. Other researchers suggest using change models to model such reciprocal variables.

In this dissertation, I used multiple analytic techniques to try to separate out cause and effect; the risk always remains, however, that the ambiguous temporal order and reciprocal nature of the processes I am trying to model will bias estimates. As human development research examines more and more complex processes, this will become an increasingly pertinent empirical issue. Researchers may need to look to other methodologies, including microanalyses, qualitative analysis, interventions, and experiments, to examine the evocative response. Identifying and quantifying the specific transactional processes that shape the evocative response will require a more finely tuned research approach than is used in this study. Behavioral genetic approaches that marshal varying degrees of genetic relatedness within a family, may also be useful.

Evocative effects, interventions, and policy

For human development and social policy, a concern with the transactional model is of more than academic interest. Our concern with improving the lives of children and their families requires a clear idea of where those improvements are best directed. Developmental models often extol the practitioner and researcher to consider the developmental context of a child when putting together interventions, but my findings suggest that the child's effects on his environment should be examined as well.

The demonstration of evocative effects have immediate implications for the design of prevention studies that target caregiver interactions with their young children. These results suggest that it may be useful to distinguish whether parenting behaviors are in response to a child's characteristics, or whether they are independent of a child's evocative characteristics. If evocative effects exist, also targeting the child's behavior or characteristics (if possible and appropriate) could be necessary to address maladaptive, reciprocal interactions. It may not be enough to merely target parents' actions when they are driven at least in part by children themselves.

My third empirical essay in particular suggests that there are policy implications of child effects. The results suggest that researchers and policy-makers might profit from considering person-context interaction for increasing program take-up and success rates. To the extent that families are competing for increasingly scarce program resources, it is arguably important to know whether or not families are competing on equal footing. Policy makers, program staff, and researchers may need to consider programs or techniques that might best address families with problems' needs. Alternatively, programs could provide better screening and counseling services for families with children with problems. One concern, however, is whether such an approach would be cost-effective. On the one hand, taking into account child effects may increase bureaucratic demand and costs; on the other, it might actually be more cost effective, as a program could target the families most at risk of failure to take-up or use the program. Further research is necessary to determine how to best address how child effects might play out in program implementation and efficacy.

The results from the first two studies are less straight-forward. Results from my study on the evocative effects on the home learning environment suggest that children's reading, math, or vocabulary proclivities play a do help shape the home learning environment, but it is unclear how this might be policy relevant, except that it might be harder to change the quality of the home learning environment than previously suspected. The pattern of results in the first essay suggest that caregivers do respond to children's language propensities, which caries some policy relevance. Training child care workers to create high-quality language environments for all charges, as well as language environments that fit individual children's developmental needs, remains a critical task for the quality of American children's child care experience. An even more active strategy would to train child care workers to more closely monitor their own language interaction with children with delayed language skills, and to the extent they are interacting or speaking with them less, provide greater language stimulation. Research is yet needed, though to determine whether the evocative effects children have are adapative (creating appropriate environments) or maladaptive (entrenching current habits and disadvantages) and this distinction is worthy of discussion.

Evocative effects on other developmental domains

My work concerning the evocative effects of children on home and child care learning environments has implications for other developmental domains as well. One in particular is education and the classroom environment. Multiple types of evocative effects could be examined in the classroom context. For example, how does child motivation or interest influence the quality of instruction he is exposed to? How does child behavior influence classroom dynamics and teacher quality? Classroom studies may use randomization, or the natural variation that occurs in a classroom, to examine how child attributes impact teaching, learning, or other aspects of classroom climate. Evocative effects could also be studied with respect to child nutrition, physical activity, and other important developmental domains, with the aim of determining the extent to which these effects occur in each domain, the degree of influence these effects have on ongoing child development, and… (what other questions do you want to answer re: evocative effects?? A little more on what is left to be done here). An exciting future for research on evocative effects – its methodological challenges, effects on other aspects of development, and implications for policy – lies ahead of us.

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TABLES

Table 2.1

Description of Sample and Analysis Variables (N=1364)

	5 months		15 months		24 months		36 months		54 months	
	M	SD	M	SD	M	SD	M	SD	M	SD
ORCE language stimulation			0.00	1.00	50.64	27.18	58.41	30.74	36.55	17.86
Time in child care										
Hours per week	19.85	18.95	21.33	18.87	22.48	18.86	23.52	18.39	25.05	15.87
Hours per week for those in care	30.64	15.25	30.80	15.61	31.06	15.32	29.55	15.88	27.80	14.57
Change in hours			1.47	16.47	1.15	16.05	1.05	15.80	1.52	16.12
In parent care	47%		47%		44%		38%		31%	
In home care	44%		42%		39%		33%		20%	
In center care	9%		11%		17%		29%		49%	
Moved into center care			5%		9%		16%		27%	
Left parental care			12%		13%		14%		18%	
Child language and cognitive devp't										
Language or Cognitive Measure			0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00
Child behavior and temperament										
Mother's assess of temperament	3.18	0.40								
Activity level	2.45	0.57			2.73	0.61				
Engagement with mother			2.53	0.68	2.82	0.74				
Negative mood	1.42	0.69	1.26	0.56	1.43	0.70				

Table 2.1 (continued)

Description of Sample and Analysis Variables

	5 months		15 months		24 months		36 months		54 months	
	M	SD	M	SD	M	SD	M	SD	M	SD
Child behavior and temperament characteristics, cont.										
Positive mood	2.52	0.63	2.49	0.64	2.78	0.67				
Sustained attention					2.99	0.66				
Affection towards mother							4.81	1.26		
Enthusiasm							4.97	1.05		
Negativity							1.68	1.10		
Persistence							5.24	1.15		
CBCL behavioral score					36.40	17.67	36.67	18.01		
Child's distress in strange situation			9.90	3.62						
Sleep problems	17%		13%		12%		9%			
Other child characteristics										
Gender (male=1)	0.52	0.50								
Child is African-American	0.13	0.33								
Child is Hispanic	0.06	0.24								
Child is White	0.76	0.42								
Child is Other race	0.05	0.21								

Table 2.1 (continued)

Description of Sample and Analysis Variables

	5 months		15 months		24 months		36 months		54 months	
	M	SD	M	SD	M	SD	M	SD	M	SD
Family characteristics										
Maternal education (years)	14.23	2.51								
Maternal age	28.11	5.63								
Partner in household	85%				85%		84%		84%	
Income/poverty threshold	3.50	3.07			3.50	2.96	3.49	2.91	3.50	2.88
Maternal stimulation of development at 6 months	2.60	0.64								
Maternal sensitivity at 6 months	9.20	1.78								
Maternal depressive symptoms at 6	9.08	8.41								
Maternal IQ (PPVT)	98.08	18.65								
HOME	6.86	1.48								
Other child care characteristics										
Caregiver education			2.57	1.09	2.64	1.05	2.87	1.09	2.72	1.05
Observed child-adult ratio			2.64	1.77	3.44	2.28	4.69	3.17	6.50	3.29

Note. PPVT= Peabody Picture Vocabulary Test; HOME= Home Observation for the Measurement of the Environment; ORCE = Observational Record of the Caregiving Environment

Table 2.2

Correlations Between Child Language/Cognitive Development and Language Stimulation Measures

		1	2	3	4	5	6	7	8	9
1	Bayley 15 months	1.00								
2	Bayley 24 months	0.51**	1.00							
3	Reynell Vocabulary Comprehension 36 months	0.42**	0.68**	1.00						
4	Reynell Expressive Language 36 months	0.28**	0.50**	0.55**	1.00					
5	Woodcock Johnson Verbal 54 months	0.39**	0.55**	0.65**	0.46**	1.00				
6	Language Stimulation 15 months	0.17**	0.22**	0.23**	0.27**	0.25**	1.00			
7	Language Stimulation 24 months	0.15**	0.23**	0.28**	0.18**	0.24**	0.54**	1.00		
8	Language Stimulation 36 months	0.06*	0.11**	0.11*	0.09*	0.13**	0.39**	0.50**	1.00	
9	Language Stimulation 54 months	-0.01	0.03	-0.07	0.03	-0.02	0.06*	0.12**	0.20**	1.00

* significant at 5%; ** significant at 1%

Table 2.3

Language Stimulation Predicted by Child's Prior Language or Cognitive Scores

	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
	Language Stimulation at 24 months		Language Stimulation at 36 months		Language Stimulation at 54 months	
Child characteristics - 15 months						
Bayley score	0.133**	0.102**				
	(0.041)	(0.035)				
Child characteristics - 24 months						
Bayley score			0.104**	0.072		
			(0.040)	(0.044)		
Child characteristics - 36 months						
Reynell: vocabulary comprehen.					-0.114*	-0.148**
					(0.045)	(0.053)
Reynell: expressive language					0.101*	0.121**
					(0.050)	(0.046)
Battery of controls	none	all	none	all	none	all
R2	0.018	0.410	0.015	0.304	0.018	0.131
Observations	748	748	832	832	914	914

Standard errors in parentheses

* significant at 5%; ** significant at 1%

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Table 2.4

Language Stimulation Predicted by Child's Contemporaneous Language or Cognitive Scores

	Model 1	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
	15 months	24 months		36 months		54 months	
Bayley Score (15 mos)	0.117**						
	(0.035)						
Bayley Score (24 mos)		0.241**	0.151**				
		(0.043)	(0.047)				
Reynell: vocabulary comprehension (36 mos)				0.063	-0.025		
				(0.051)	(0.055)		
Reynell: expressive language (36 mos)				-0.004	0.006		
				(0.042)	(0.045)		
Woodcock-Johnson language (54 mos)						-0.019	-0.027
						(0.045)	(0.059)
Prior language stimulation			0.335**		0.403**		0.141**
			(0.044)		(0.042)		(0.053)
Battery of controls	all	all	all	all	all	all	all
R^2	0.511	0.450	0.545	0.325	0.468	0.128	0.188
Observations	704	748	581	832	647	914	686

Standard errors in parentheses

* significant at 5%; ** significant at 1%

Table 2.5

Change Score Regression of Language Stimulation on Child's Language or Cognitive Scores

	Change in language stimulation from 15-24 months	Change in language stimulation from 24-36 months	Change in language stimulation from 36-54 months
Change in cognitive scores from 15-24 months	0.082*		
	(0.040)		
Change in cognitive scores from 24-36 months		0.042	
		(0.022)	
Change in cognitive scores from 36-54 months			0.002
			(0.032)
Observations	581	647	686

Standard errors in parentheses
All models include time variant controls
* significant at 5%; ** significant at 1%

Table 2.6
Results from Full Models

	Language stimulation at 15 months	Language stimulation at 24 months	Language stimulation at 36 months	Language stimulation at 54 months
Bayley score (15, 24 months)	0.117**	0.151**		
	(0.035)	(0.047)		
Language comprehension score (36 months)			-0.025	
			(0.055)	
Expressive language score (36 months)			0.006	
			(0.045)	
Woodcock Johnson score (54 months)				-0.027
				(0.059)
Prior language stimulation score		0.335**	0.403**	0.141**
		(0.044)	(0.042)	(0.053)
Child is male	-0.054	-0.017	0.019	0.022
	(0.067)	(0.073)	(0.074)	(0.092)
Child is black	-0.016	-0.293+	-0.216	-0.415*
	(0.137)	(0.163)	(0.167)	(0.181)
Child is hispanic	0.068	-0.233	0.292+	-0.289
	(0.150)	(0.155)	(0.162)	(0.197)
Child is other race	0.086	0.025	0.035	-0.001
	(0.162)	(0.181)	(0.220)	(0.232)
Child temperament	0.066	0.132	0.033	0.174
	(0.088)	(0.099)	(0.098)	(0.123)
Maternal education	-0.042*	-0.010	-0.037+	0.044
	(0.020)	(0.021)	(0.022)	(0.027)
Maternal PPVT score	0.000	-0.005+	0.001	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Maternal age	-0.007	0.013	-0.014	-0.007
	(0.008)	(0.009)	(0.009)	(0.011)
Maternal stimulation at 6 months	0.025	0.022	-0.034	0.003
	(0.058)	(0.061)	(0.062)	(0.076)
Maternal sensitivity at 6 months	0.045+	0.014	0.048+	0.012
	(0.023)	(0.025)	(0.025)	(0.031)
Maternal depression at 6 months	-0.001	0.004	-0.008	0.003
	(0.005)	(0.005)	(0.005)	(0.007)
Income to needs ratio	0.039**	0.028*	0.025+	-0.022
	(0.013)	(0.014)	(0.014)	(0.018)
Proportion of time partner in household	0.227+	0.025	0.059	-0.106
	(0.124)	(0.138)	(0.142)	(0.183)
Home environment, 15 months	0.067*	-0.001		
	(0.031)	(0.037)		

Table 2.6, continued

Results from Full Models

	Language stimulation at 15 months	Language stimulation at 24 months	Language stimulation at 36 months	Language stimulation at 54 months
Home language stimulation, 36 and 54 months			0.037	0.008
			(0.044)	(0.089)
Home learning environment, 36 and 54 months			0.025	0.009
			(0.022)	(0.044)
Home academic environment 54 months only				0.029
				(0.053)
Site 1	0.009	-0.522**	-0.151	-0.092
	(0.148)	(0.162)	(0.161)	(0.211)
Site 2	0.166	0.238	-0.127	-0.087
	(0.152)	(0.161)	(0.167)	(0.208)
Site 3	0.419**	0.101	-0.104	-0.232
	(0.158)	(0.180)	(0.183)	(0.229)
Site 4	0.236	-0.004	0.088	-0.006
	(0.152)	(0.169)	(0.167)	(0.225)
Site 5	0.218	0.152	-0.269	0.053
	(0.156)	(0.169)	(0.174)	(0.224)
Site 6	0.056	-0.081	-0.143	-0.483*
	(0.175)	(0.192)	(0.189)	(0.228)
Site 7	-0.098	0.020	0.097	-0.012
	(0.153)	(0.168)	(0.161)	(0.208)
Site 8	0.184	0.105	-0.072	-0.417*
	(0.142)	(0.158)	(0.156)	(0.205)
Site 9	-0.103	-0.044	-0.142	-0.172
	(0.149)	(0.163)	(0.158)	(0.200)
Observed child-adult ratio	-0.282**	-0.191**	-0.123**	-0.059**
	(0.022)	(0.022)	(0.017)	(0.017)
Hours in care	-0.008**	0.002	-0.003	0.002
	(0.003)	(0.003)	(0.003)	(0.004)
Caregiver education	0.059+	0.040	0.079+	0.058*
	(0.035)	(0.041)	(0.041)	(0.023)
In home care dummy	0.402**	0.083	-0.003	0.402**
	(0.085)	(0.097)	(0.108)	(0.114)
Constant	-0.293	-0.055	0.406	-1.456
	(0.488)	(0.581)	(0.618)	(0.914)
Observations	704	581	647	686
R-squared	0.511	0.545	0.468	0.188

Standard errors in parentheses

* significant at 5%; ** significant at 1%

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Table 3.1

Description of Sample, Developmental Measures, and HOME Outcome Measure, at Time of First Assessment (N=7886)

	Mean	Std. Dev.	Min	Max
Child characteristics (at baseline)				
Child is male	51%		0	1
Child is non-Black, non-Hispanic	80%		0	1
Child is black	15%		0	1
Child is Hispanic	6%		0	1
Child birth order	1.92	1.07	1	11
Child age in years	3.05	2.97	0	18.6
Child was of low birth-weight	7%			
Average PPVT score	0.29	0.96	-3.57	3.48
Average PIAT math score	0.19	1.00	-2.54	2.98
Average PIAT reading score	0.15	1.01	-5.64	2.36
Family characteristics (at baseline)				
Household income	$43, 370	$8,177	0	$97,410
Family lives in urban area	75%		0	1
Number of children in the family	2.85	1.30	1	11
Married	76%		0	1
Maternal age	29.22	4.63	21	47
Maternal highest grade completed at first assessment	12.82	2.43	0	20
Maternal AFQT score	45.01	27.98	1	99
Grandparents' highest grade completed	11.31	2.8	0	20

Values in table are weighted

Table 3.2

NLSY "Standardized" HOME Scores, by Age

Child's Age in Years	Mean	Std. Dev
Age 0	979.7	154.0
Age 1	971.9	166.0
Age 2	973.5	163.9
Age 3	964.8	169.7
Age 4	963.9	170.0
Age 5	968.1	167.8
Age 6	970.3	160.0
Age 7	970.5	160.1
Age 8	970.7	160.8
Age 9	973.4	158.9
Age 10	987.5	155.6
Age 11	983.5	154.6
Age 12	972.6	156.8
Age 13	958.2	158.7
Age 14	948.1	155.5
Age 15	934.9	160.4
Age 16	927.0	150.0
Age 17	901.3	165.3

Table 3.3

Correlations Between Key Outcome and Predictor Variables

	Math score	Read score	PPVT score	HOME	Child age	Male	Black	Hisp.	Low brth wgt	Birth order	# kids	Mat. age	Mar-ried	Income	Mat. Educ.	Pat. Educ	Mat cog score
Math score	1.00																
Reading score	0.70	1.00															
PPVT score	0.64	0.63	1.00														
HOME	0.40	0.41	0.48	1.00													
Child age	-0.17	-0.23	-0.07		1.00												
Male						1.00											
Black	-0.26	-0.25	-0.33	-0.22	0.18		1.00										
Hispanic	-0.11		-0.16	-0.16			-0.32	1.00									
Low birthwgt									1.00								
Birth order	-0.13	-0.17	-0.23	-0.29	-0.27		0.07	0.07	0.00	1.00							
# Children	-0.20	-0.23	-0.27	-0.30			0.11	0.12		0.62	1.00						
Maternal age	0.23	0.18	0.14		-0.17					0.32							
Married	0.27	0.27	0.29	0.34	-0.18		-0.40			-0.07	-0.10	0.21	1.00				
Income	0.30	0.25	0.26	0.28	-0.16		-0.18				-0.09	0.33	0.35	1.00			
Maternal educ.	0.30	0.26	0.35	0.34	-0.13			-0.45		-0.10	-0.17	0.19	0.13	0.25	1.00		
Paternal educ.	0.30	0.27	0.34	0.34	-0.14		-0.08	-0.35		-0.10	-0.17	0.21	0.15	0.26	0.65	1.00	
Mat cog score	0.50	0.47	0.51	0.43	-0.18		-0.36	-0.21		-0.12	-0.19	0.30	0.37	0.39	0.47	0.48	1.00

All correlations shown are significant at $p < .05$

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Table 3.4

Correlation in HOME Scores Across Time

	1986	1988	1990	1992	1994	1996	1998	2000	2002	2004
1986	1.00									
1988	0.50	1.00								
1990	0.44	0.53	1.00							
1992	0.41	0.48	0.56	1.00						
1994	0.39	0.44	0.50	0.56	1.00					
1996	0.34	0.40	0.43	0.50	0.57	1.00				
1998	0.32	0.38	0.41	0.47	0.52	0.56	1.00			
2000	0.37	0.28	0.38	0.41	0.48	0.50	0.55	1.00		
2002	.	0.24	0.33	0.37	0.43	0.45	0.52	0.59	1.00	
2004	.	.	0.13	0.29	0.42	0.39	0.53	0.52	0.58	1.00

All scores are correlated at $p < .001$

Table 3.5

Correlation in HOME Scores Between Children in the Same Family

	HOME Child 1	HOME Child 2	HOME Child 3	HOME Child 4	HOME Child 5	HOME Child 6
HOME						
Child 1	1.00					
N	4261					
HOME						
Child 2	0.77	1.00				
N	3232	3308				
HOME						
Child 3	0.72	0.77	1.00			
N	1519	1542	1585			
HOME						
Child 4	0.69	0.75	0.83	1.00		
N	547	548	556	578		
HOME						
Child 5	0.64	0.71	0.78	0.80	1.00	
N	185	186	186	189	200	
HOME						
Child 6	0.60	0.58	0.64	0.73	0.72	1.00
N	67	68	68	68	73	75

All scores are correlated at $p < .001$

Table 3.6

Correlations in the Differences within Family on HOME Scores and Cognitive Scores

	1	2	3	4
Difference in HOME	1.00			
Difference in Reading score	0.16** 0.00	1.00		
Difference in math score	0.15** 0.00	0.53** 0.00	1.00	
Difference in PPVT score	0.16** 0.00	0.43** 0.00	0.42** 0.00	1.00

** $p < .01$

Table 3.7

OLS Regression Examining the Influence of Children's Scores on the Home Learning Environment

	(1)	(2)	(3)	(4)
Math PIAT	0.083**			0.048**
	(0.007)			(0.009)
Reading PIAT		0.078**		0.063**
		(0.009)		(0.010)
PPVT			0.117**	
			(0.013)	
Lagged HOME score	0.446**	0.462**	0.341**	0.467**
	(0.009)	(0.010)	(0.013)	(0.010)
Child is male	-0.116**	-0.109**	-0.114**	-0.122**
	(0.013)	(0.013)	(0.019)	(0.014)
Child's age	-0.004	-0.013**	0.009+	0.020**
	(0.003)	(0.004)	(0.005)	(0.004)
Child is Black	-0.077**	-0.077**	-0.059*	-0.067**
	(0.019)	(0.020)	(0.029)	(0.021)
Child is Hispanic	-0.120**	-0.129**	-0.136**	-0.128**
	(0.023)	(0.023)	(0.037)	(0.024)
Child was of low birthweight	0.011	0.007	0.093*	0.012
	(0.025)	(0.026)	(0.041)	(0.027)
Child's birth order	-0.023**	-0.027**	-0.022	-0.027**
	(0.009)	(0.010)	(0.014)	(0.010)
Total # of children	-0.019**	-0.015*	-0.030**	-0.015*
	(0.006)	(0.006)	(0.009)	(0.006)
Maternal age	-0.012**	-0.013**	-0.006*	-0.013**
	(0.002)	(0.002)	(0.003)	(0.002)
Maternal cog score	0.002**	0.002**	0.002**	0.001**
	(0.000)	(0.000)	(0.001)	(0.000)
Maternal education	0.032**	0.033**	0.037**	0.033**
	(0.004)	(0.004)	(0.006)	(0.004)
Grandparent education	0.012**	0.008**	0.011*	0.008**
	(0.003)	(0.003)	(0.004)	(0.003)
Marital status	0.221**	0.202**	0.297**	0.210**
	(0.016)	(0.017)	(0.025)	(0.018)
Family income	0.006**	0.006**	0.004**	0.006**
	(0.001)	(0.001)	(0.001)	(0.001)
Urban residence	0.077**	0.068**	0.083**	0.068**
	(0.014)	(0.015)	(0.022)	(0.016)
Constant	-0.112+	0.062	-0.491**	-0.268**
	(0.064)	(0.072)	(0.106)	(0.074)
Observations	16278	12938	7180	12855
R-squared	0.413	0.422	0.357	0.424

Standard errors have been adjusted using Huber-White methods.

+ p <.10. * p <.05. ** p <.01.

Table 3.8

Comparison of Linear, Dummy and Exponential Models using Lagged OLS Regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Math	0.083**	0.083**							
	(0.007)	(0.008)							
Math^2		-0.001							
		(0.004)							
Math 25-50%			0.094**						
			(0.021)						
Math 50-75%			0.144**						
			(0.021)						
Math 75-100%			0.213**						
			(0.021)						
Read				0.078**	0.077**				
				(0.009)	(0.008)				
Read^2					-0.012*				
					(0.005)				
Read 25-50%						0.106**			
						(0.022)			
Read 50-75%						0.171**			
						(0.022)			
Read 75-100%						0.184**			
						(0.023)			
PPVT							0.117**	0.116**	
							(0.013)	(0.014)	
PPVT^2								0.002	
								(0.007)	
PPVT 25-50%									0.099**
									(0.036)
PPVT 50-75%									0.180**
									(0.037)
PPVT 75-100%									0.285**
									(0.039)
Constant	-0.112+	-0.112+	-0.225**	0.062	0.073	-0.047	-0.491**	-0.491**	-0.639**
	(0.064)	(0.064)	(0.067)	(0.072)	(0.072)	(0.075)	(0.106)	(0.106)	(0.111)
Number of obs	16278	16278	16278	12938	12938	12938	7180	7180	7180
R2	0.413	0.413	0.413	0.422	0.423	0.422	0.357	0.358	0.357

Standard errors have been adjusted using Huber-White methods.
All models include full battery of controls.
+ $p < .10$. * $p < .05$. ** $p < .01$.

Table 3.9

Does Age Matter for Evocative Effects?

	(1) Young	(2) Old	(3) Young	(4) Old
Math PIAT	0.036*	0.036**		
	(0.015)	(0.009)		
Reading PIAT	0.039*a	0.072**		
	(0.016)	(0.010)		
PPVT			0.132**	0.105**
			(0.026)	(0.017)
R-squared	0.449	0.420	0.384	0.388

Standard errors have been adjusted using Huber-White methods.

[a] Coefficient is significantly different from other at $p < 0.05$.

[b] Coefficient is significantly different from other at $p < 0.01$.

+ p <.10. * p <.05. ** p <.01.

Table 3.10

Does Gender Matter for Evocative Effects?

	(1) F	(2) M	(3) F	(4) M
Math PIAT	0.058**a	0.025*		
	(0.012)	(0.011)		
Reading PIAT	0.046**	0.066**		
	(0.013)	(0.011)		
PPVT			0.119**	0.114**
			(0.020)	(0.020)
R-squared	0.419	0.422	0.391	0.373

Standard errors have been adjusted using Huber-White methods.

[a] Coefficient is significantly different from other at $p < 0.05$.

[b] Coefficient is significantly different from other at $p < 0.01$.

+ p <.10. * p <.05. ** p <.01.

Table 3.11

Does Maternal Education Matter for Evocative Effects?

	(1) Low Ed	(2) High Ed	(3) Low Ed	(4) High Ed
Math PIAT	0.025*b	0.060**		
	(0.011)	(0.011)		
Reading PIAT	0.076**a	0.044**		
	(0.011)	(0.012)		
PPVT			0.114**	0.116**
			(0.020)	(0.021)
R-squared	0.380	0.399	0.332	0.353

Standard errors have been adjusted using Huber-White methods.

[a] Coefficient is significantly different from other at $p < 0.05$.

[b] Coefficient is significantly different from other at $p < 0.01$.

+ $p < .10$. * $p < .05$. ** $p < .01$.

Table 3.12

Does Income Matter for Evocative Effects?

	(1) Low income	(2) High income	(3) Low income	(4) High income
Math PIAT	0.029*	0.048**		
	(0.012)	(0.012)		
Reading PIAT	0.061**	0.071**		
	(0.012)	(0.013)		
PPVT			0.121**	0.110**
			(0.020)	(0.020)
R-squared	0.376	0.356	0.314	0.301

Standard errors have been adjusted using Huber-White methods.

[a] Coefficient is significantly different from other at $p < 0.05$.

[b] Coefficient is significantly different from other at $p < 0.01$.

+ p <.10. * p <.05. ** p <.01.

Table 3.13

Individual Fixed Effect Regression Examining the Influence of Children's Scores on the Home Environment

	(1)	(2)
Math PIAT	0.024*	
	(0.010)	
Read PIAT	0.033**	
	(0.010)	
PPVT		0.050**
		(0.015)
Child age	0.005*	0.010**
	(0.002)	(0.002)
Marital status	0.185**	0.127**
	(0.025)	(0.030)
Urban status	0.049+	0.066+
	(0.025)	(0.035)
Income	0.002	0.001
	(0.001)	(0.001)
Maternal education	-0.021	0.009
	(0.017)	(0.020)
Constant	0.093	-0.282
	(0.211)	(0.250)
Observations	19707	14616
Number of id	7732	8083
R-squared	0.007	0.009

Standard errors have been adjusted using Huber-White methods.

+ p <.10. * p <.05. ** p <.01.

Table 3.14

Family Fixed Effects Regression Examining the Influence of Child Cognitive Scores on the Home Learning Environment

	(1)	(2)
Math	0.053**	
	(0.011)	
Reading	0.047**	
	(0.011)	
PPVT		0.086**
		(0.010)
Child is male	-0.081**	-0.081**
	(0.011)	(0.011)
Child age	0.020**	0.003
	(0.005)	(0.005)
Birth order	-0.094**	-0.075*
	(0.031)	(0.031)
Maternal education	-0.023	-0.017
	(0.024)	(0.025)
Income	-0.005	-0.006
	(0.004)	(0.005)
Married	0.103+	0.134*
	(0.061)	(0.061)
Family size	0.001	-0.035*
	(0.017)	(0.017)
Constant	0.045	0.058+
	(0.031)	(0.032)
Observations	2613	2861
R-squared	0.065	0.052

Standard errors have been adjusted using Huber-White methods.

+ p <.10. * p <.05. ** p <.01.

Table 3.15

Results from Multilevel Model Predicting HOME Cognitive Score

		Model 1	Model 2	Model 3	Model 4
Fixed Effects					
Level, π_{0i}	Intercept	0.007	-0.096**	-0.128**	-0.124**
		(0.009)	(0.022)	(0.027)	(0.027)
	Current Reading score		0.076**		0.077**
			(0.008)		(0.010)
	Current Math score		0.060**		0.048**
			(0.008)		(0.010)
	Prior Reading score			0.048**	0.021*
				(0.010)	(0.010)
	Prior Math score			0.053**	0.029**
				(0.010)	(0.010)
	Change in Reading score				
	Change in Math score				
Variance Components					
Level 1	Within-person	0.571	0.306	0.318	0.314
		(0.012)	(0.008)	(0.010)	(0.010)
Level 2	In initial stauts	0.411	0.407	0.388	0.385
		(0.005)	(0.005)	(0.007)	(0.007)
	In rate of change				
	Covariance				
Log-liklehood		-29458	-22339	-14553	-14733

All conditional models run with full battery of controls.

Table 4.1

Summary Statistics (N=2938)

	Percentage
Outcome variable	
Household took-up voucher	52.2%
Child health characteristics	
Physical, emotional, or mental problems that requires medicine	17.5%
Physical, emotional, or mental problems that make it hard to go to school	6.6%
Physical, emotional, or mental problems that make it hard to play active games or sports	11.5%
Low birth weight	10.3%
Was in the hospital before his/her first birthday because sick or injured	14.4%
Child learning and behavioral problem characteristics	
Goes to a special class because of behavior problems	12.2%
Provoked a call from the school about schoolwork or behavior	31.0%
Has been suspended or expelled in last two years	15.7%
Goes to a special class because of learning problems	22.2%
Goes to a special class for gifted students or does advanced work in any subject	18.0%
Child problem index	
Total number of child problems	141.4%
No child problems	40.1%
One child problem	22.1%
Two child problems	16.0%
Three child problems	9.8%
Four child problems	6.0%
Five child problems	3.6%
Six child problems	2.0%
Child demographic characteristics	
Male child	59.9%
Child age 5 or under	69.0%
Child aged 6-12	41.5%
Child 13 and over	42.0%
Non-birth child	13.0%

Table 4.2

Logistic Regression of Take-up on Child Characteristics

	Full sample (N=2938)
Presence in the household of a child:	
Physical, emotional, or mental problems that requires medicine	0.108
	(0.132)
Physical, emotional, or mental problems that make it hard to go to school	-0.382**
	(0.193)
Physical, emotional, or mental problems that make it hard to be active	0.057
	(0.165)
Low birth weight	-0.306**
	(0.143)
Was in the hospital before his/her first birthday of sickness/injuy	0.095
	(0.129)
Goes to a special class because of behavior problems	-0.056
	(0.152)
Provoked a call from the school the parent about schoolwork or behavior	-0.129
	(0.113)
Suspended or expelled in last two years	-0.023
	(0.137)
Goes to a special class because of learning problems	-0.086
	(0.120)
Goes to a special class for gifted students/does advanced work in any subjects	0.058
	(0.112)
Male child	-0.037
	(0.103)
Child aged 5 or under	0.014
	(0.242)
Child aged 6-12	0.015
	(0.148)
Child 13 and over	-0.001
	(0.123)
Non-birth child	0.154
	(0.140)
Pseudo R2	0.111

Note: Standard errors in parentheses.

Note: All models include household controls.

* p<.10; *** p<.05; ***p<.01.

Table 4.3

Logistic Regression of Take-up on Child Problem Indices and Controls

	Linear measure	Dummy measure	2+ Dummy measure
Cumulative child problem index	-0.056**		
	(0.028)		
No child problems		*Reference Group*	
One child problem		0.004	
		(0.109)	
Two child problems		-0.214*	
		(0.124)	
Three child problems		-0.122	
		(0.148)	
Four child problems		-0.153	
		(0.183)	
Five child problems		-0.060	
		(0.231)	
Six or more child problems		-0.566**	
		(0.281)	
Two or more child problems			-0.185**
			(0.091)
Constant	0.225	-0.202	0.256
	(0.529)	(0.681)	(0.529)
Pseudo R2	0.107	0.108	0.107

Note: Standard errors in parentheses.
Note: All models include household controls.
* p<.10; *** p<.05; ***p<.01.

APPENDIX

Appendix Table 1.*Summary Statistics for Control Variables*

	Mean	Std. Dev.
Experimental (MTO) group	0.59	0.49
Boston	0.22	0.41
Baltimore	0.15	0.36
Chicago	0.23	0.42
Los Angeles	0.14	0.35
New York	0.26	0.43
Adult is aged 19-29	0.15	0.35
Adult is aged 30-39	0.45	0.50
Adult is aged 40-49	0.29	0.45
Adult is aged 50-59	0.12	0.33
Adult is black	0.65	0.47
Adult is other race	0.28	0.44
Adult is Hispanic ethnicity	0.30	0.46
Adult graduated from high school	0.39	0.49
Adult has never been married	0.62	0.48
Adult gets AFDC	0.93	0.26
Adult was a parent before age 18	0.26	0.43
Adult lived with both parents at age 16	0.45	0.50
Adult's mother got AFDC	0.50	0.50
Adult has car	0.16	0.37
Adult has driver's license	0.32	0.47
Adult previously applied for Section 8	0.41	0.49
Adult has moved more than three times in last 5 years	0.08	0.28
Number of years adult has lived in neighborhood	10.05	9.48
Number of years adult has lived in apartment	6.22	6.78
Desire to live with African American and White families	0.50	0.50
Desire to live with African American and Hispanic families	0.60	0.49
Desire to live with Hispanic and White	0.32	0.47
Desire to live with all races	0.52	0.50
Desire to live with mostly white families	0.17	0.37
Household total	3.84	1.56
Number of children age 6-17	1.63	1.24
Number of children age 0-5	0.88	0.93
Want to live in different apartment in same neighborhood	0.06	0.25
Want to live in different neighborhood	0.57	0.49
Want to live in suburbs	0.17	0.37
Wants to live in different city	0.16	0.37
Overall positive feeling for moving	-0.02	0.68
Wants to move to have a new apartment	0.45	0.50

Appendix Table 1 (continued). *Summary Statistics for Control Variables*

	Mean	Std. Dev.
Wants to move to have better schools	0.48	0.50
Wants to move to find new job	0.06	0.23
Wants to move for other reason	0.10	0.30
Wants to move to be closer to current job	0.01	0.09
Wants to move to get away from drugs	0.75	0.43
Network score	0.00	0.53
Parental involvement score	-0.01	0.83
Neighborhood derelict score	0.00	0.53
Apartment derelict score	0.01	0.59
Spent last week working	0.23	0.42
Spent last week looking for a job	0.14	0.35
Spent last week in school	0.10	0.29
Spend last week doing small job	0.12	0.32
Currently gets AFDC	0.75	0.44
Currently gets food stamps	0.80	0.40
Currently gets SSI	0.17	0.38
Currently gets child support	0.14	0.35
Currently gets Medicaid	0.69	0.46
Currently gets educational assistance	0.09	0.28
Currently gets WIC	0.33	0.47
Currently gets unemployment	0.02	0.13
Currently gets Social Security disability	0.08	0.28

Appendix Table 1. *Full Model*

	Full sample (N=2938)
Experimental group	-0.507***
	(0.084)
Boston	0.139
	(0.140)
Baltimore	0.597***
	(0.180)
Chicago	-0.231
	(0.168)
Los Angeles	1.111***
	(0.161)
Between the ages of 19-29	0.527***
	(0.149)
Between the ages of 40-49	-0.369***
	(0.109)
Aged 50+	-0.646***
	(0.168)
Black	-0.111
	(0.203)
Other	-0.218
	(0.176)
Hispanic	-0.196
	(0.158)
Graduated from high school	0.090
	(0.089)
Never been married	-0.074
	(0.097)
Received AFDC in the past	-0.096
	(0.177)
Parent before age 18	0.159
	(0.105)
Lived with both parents at age 16	-0.142*
	(0.086)
Mother got AFDC	0.027
	(0.092)
Has a car	0.159
	(0.136)
Has a license	0.055
	(0.104)

Appendix Table 1 (continued). *Full Model*

	Full sample (N=2938)
Previously applied for Section 8	0.243***
	(0.086)
Moved three times	0.200
	(0.152)
Length of time in neighborhood	-0.005
	(0.006)
Length of time in apartment	0.012
	(0.008)
Lived in neighborhood with AA and whites	0.127
	(0.106)
Lived in neighborhood with AA and Hispanic	0.069
	(0.123)
Lived in in neighborhood with hispanics and whites	-0.094
	(0.117)
Lived in neighborhood with a mix of races	-0.127
	(0.111)
Lived in neighborhood with mostly whites	0.119
	(0.124)
Total number in household	0.006
	(0.068)
Total number of children aged 6-17 household	-0.052
	(0.089)
Total number of children aged 0-5 household	-0.186*
	(0.106)
Would like to move to new apartment in same neighborhood	-0.334
	(0.333)
Would like to move to new neighborhood	0.032
	(0.294)
Would like to move to the suburbs	0.090
	(0.306)
Would like to move to a new city	0.004
	(0.307)
Overall feeling about moving	0.432***
	(0.083)
Primary reason to move - Apartment	0.023
	(0.140)
Primary reason to move - Schools	0.059
	(0.139)

Appendix Table 1 (continued). *Full Model*

	Full sample (N=2938)
Primary reason to move - Find a new job	-0.113
	(0.215)
Primary reason to move - Other	-0.027
	(0.189)
Primary reason to move - For job	0.200
	(0.457)
Primary reason to move - Drugs	0.054
	(0.147)
Network score	-0.144*
	(0.082)
Parental involvement score	0.089
	(0.060)
Neighborhood quality score	-0.252***
	(0.096)
Apartment quality score	0.093
	(0.079)
In school	0.356**
	(0.154)
Looking for a job	-0.078
	(0.127)
Working	0.029
	(0.127)
Does small jobs	0.198
	(0.127)
Currently gets AFDC	0.181
	(0.153)
Currently gets food stamps	0.102
	(0.154)
Currently gets SSI	-0.009
	(0.125)
Currently gets child support	0.096
	(0.119)
Currently gets Medicaid	-0.056
	(0.108)
Currently gets educational assistance	-0.090
	(0.155)
Gets WIC	-0.007
	(0.110)

Appendix Table 1 (continued). *Full Model*

	Full sample (N=2938)
Gets unemployment	0.426
	(0.317)
Gets disability	-0.176
	(0.159)
Male child	-0.037
	(0.103)
Child age 5 or under	0.014
	(0.242)
Child aged 6-12	0.015
	(0.148)
Child aged 13 and over	-0.001
	(0.123)
Non-birth child	0.154
	(0.140)
Physical, emotional, or mental problems that requires medicine	0.108
	(0.132)
Physical, emotional, or mental problems that make it hard to go to school	-0.382**
	(0.193)
Physical, emotional, or mental problems that make it hard to play	0.057
	(0.165)
Low birth weight	-0.306**
	(0.143)
In the hospital before his/her first birthday	0.095
	(0.129)
Goes to a special class for gifted students/ does advanced work	0.058
	(0.112)
Child who goes to a special class because of behavior problems	-0.056
	(0.152)
Call from the school about the child's schoolwork or behavior	-0.129
	(0.113)
Has been suspended or expelled in last two years	-0.023
	(0.137)
Goes to a special class because of learning problems	-0.086
	(0.120)
Constant	0.431
	(0.592)
Pseudo R2	0.111

Note: Standard errors in parentheses.
* p<.10; *** p<.05; ***p<.01.