

CONDITIONS FOR EFFECTIVE KNOWLEDGE ACQUISITION

by

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DEDICATION

For my mother, Wanda McBurl-Atkins,
the McBurl clan in Oklahoma and elsewhere, and
my pal and partner for life, Avi B. Nires.

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I owe a debt of gratitude to many individuals who, over the years, have been a positive influence on my growth as a human being. I cannot list them all, but at least two deserve special recognition. There's my Scout Master and Sunday school teacher Wallace K. Standridge, who was the best guide a young man could have in life. Whether on campouts or on religious outings, Wally provided me the opportunity to learn the value of hard work, teamwork, and leadership, skills that have served me well in the pursuit of higher education. The sun will soon set for old Wally, and age has taken some of his memories and his voice in his last days, but I hope he knows he's touched a great many individuals, myself included, and made us better people.

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year prior to the start of my graduate education at Michigan, I might never have considered sociology as a career path. David J. Harding also deserves a great deal of credit for my successful completion of the program. Taking over my mentorship after I decided to focus on quantitative methods, Dave pushed and challenged me on many fronts, helping me to improve as a scholar. I believe my writing has benefitted greatly, and my use of statistical methods perhaps more so, under Dave's tutelage. He not only guided my original research, but he also took me on as a collaborator on his original research. In both cases, I gained invaluable experience that I believe will serve as a strong foundation for my future career. A graduate student could not ask for a better mentor.

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nerve: it ain't that deep. The combination of pursuing a graduate school with all the little problems life throws at has had its challenges, but whatever they've been—and they're not worth recounting, to be sure—none of it really matters in the grand scheme of things. Trouble will not last always, the storm always passes, and in the end all things work together for good for those who love God and are called according to His purpose.

TABLE OF CONTENTS

DEDICATION.....	ii
ACKNOWLEDGEMENTS	iii
LIST OF TABLES	vii
LIST OF FIGURES	viii
CHAPTER	
1. INTRODUCTION.....	1
2. THE RELATIONSHIP BETWEEN EARLY MATERNAL AGE AND CHILDREN'S READING COMPREHENSION AND MATHEMATICS PERFORMANCE	16
3. UNDERSTANDING HOW FAMILY SOCIOECONOMIC STATUS MEDIATES THE MATERNAL INTELLIGENCE-CHILD OUTCOMES RELATIONSHIP: A MODERATED MEDIATION ANALYSIS	73
4. THE EFFECT OF PRESCHOOL INTERVENTION DEPENDS ON MATERNAL IQ: A REEVALUATION OF THE CAROLINA ABECEDARIAN PROJECT DATA	119
5. CONCLUSION: CONDITIONS FOR EFFECTIVE KNOWLEDGE ACQUISITION	160

LIST OF TABLES

Table 2.1. Family descriptive characteristics by early maternal age status and data source.	56
Table 2.2. HLM results for mathematics percentile score.	58
Table 2.3. HLM results for PIAT reading comprehension percentile score.	60
Table 2.4. Comparison of HLM and latent variable regressions for PIAT reading comprehension scores.	62
Table 3.1. Means, standard deviations, and pairwise correlations for maternal AFQT percentile score, family ses, and children's percentile scores (all measures)	103
Table 3.2. Bootstrapped indirect effects of maternal AFQT on children's percentile scores at the mean and ± 1 SD (all measures).	108
Table 4.1. Intra- and intergenerational correlation coefficients between personal characteristics and socioeconomic outcomes averaged from four studies analyzed by Jencks et al., 1979	145
Table 4.2. Means on Stanford-Binet and Wechsler instruments by age of assessment, maternal IQ class, and group assignment.	146
Table 4.3. <i>p</i>-values from Student's <i>t</i>, testing equality of means between control and treated subjects in each maternal IQ class.	147
Table 4.4. Quadratic growth curve model of child IQ scores.	148

LIST OF FIGURES

Figure 3.1. Conceptual moderated mediation model in which the independent variable moderates the mediated path.....	101
Figure 3.2. A model of simple mediation.	102
Figure 3.3. Results of regression analysis for moderated mediation of PIAT-R reading recognition outcome	104
Figure 3.4. Results of regression analysis for moderated mediation of PIAT-R reading comprehension outcome.....	105
Figure 3.5. Results of regression analysis for moderated mediation of PIAT-R mathematics outcome	106
Figure 3.6. Results of regression analysis for moderated mediation of PPVT-R outcome.	107
Figure 3.7. Moderated indirect effect of maternal AFQT percentile scores on children's PIAT-R reading recognition percentile scores through family ses with 95% confidence bands.....	109
Figure 3.8. Moderated indirect effect of maternal AFQT percentile scores on children's PIAT-R reading comprehension percentile scores through family ses with 95% confidence bands.....	110
Figure 3.9. Moderated indirect effect of maternal AFQT percentile scores on children's PIAT-R mathematics percentile scores through family ses with 95% confidence bands.....	111
Figure 3.10. Moderated indirect effect of maternal AFQT percentile scores on children's PPVT-R percentile scores through family ses with 95% confidence bands.....	112
Figure 4.1. Child IQ Score × Age × Maternal IQ × Group Assignment.	150

CHAPTER 1

INTRODUCTION

Recent years have witnessed a renewed focus on an old problem—that of the general decline of the education of American children. On the 2007 National Assessment of Educational Progress, often referred to as the Nation’s report card, 33 percent of all fourth-graders and 50 percent of the economically disadvantaged scored below basic in reading (NAEP, 2008). The passage of the bipartisan No Child Left Behind Act (NCLB; 2001) and the subsequent debate regarding its effectiveness have contributed to serious and sustained discussion among social scientists and education experts and professionals about the most efficient path to not only forestalling American education’s further decline but to improving it as well. This revived debate over the quality of American education is welcome in that it prompts the question of whether U.S. citizens will continue to be competitive in an increasingly globalized economy desperately in need of bright people, particularly those with higher-order mathematics and science skills, in addition to foreign language competence.

More concerning than the education declines alone, however, which in the long-term portend a regress in the technical knowledge necessary for sustaining the social welfare state so dependent on it, is the attendant reversal, since the late 1980s, of the closing of the racial gap in academic achievement, particularly between blacks and whites (Thernstrom & Thernstrom, 2003). While still faring better than they did relative

to whites in the 1970s, at the end of the 1990s the average black student, for instance, scored below 75 percent of all white students on most standardized tests (Jencks & Phillips, 1998). Analyzing data from the Panel Study of Income Dynamics (PSID), Yeung and Pfeiffer (2009) found that black children, before starting school, scored from a half to a little greater than three quarters of a standard deviation lower than whites on letter and applied problem tests. Phillips, Crouse, and Ralph (1998) found that the differences in achievement between blacks and whites widen as children move through elementary and secondary schooling and remain real into adulthood.

The proximal determinants of educational failure and the racial (and class) gap in achievement have run the gamut from differences in family structure (Coleman et al., 1966; Kennedy & Bumpass, 2007; McLanahan & Sandefur, 1994; Moynihan, 1965) to disparities in resource allocation to schools (Condrón & Roscigno, 2003) to parenting quality (Conger, Conger, & Elder, 1997; Conger, Ge, Elder, Lorenz, & Simmons, 1994), just to name a few factors (for a general overview of factors contributive to child outcomes, see Grusec & Hastings, 2007). And over the course of the past four decades, many of these factors have served as the foundation of policy prescriptions designed to achieve parity between those at the lowest and highest ends of educational and cognitive achievement. Given both the continuing decline of American education, generally, and the continuing widening of the racial gap in achievement, it is fair to say that scholars need to refine old theories to both better understand how development works and to create policies that will actually close achievement gaps in whatever domain they exist.

Achievement Inequality and Why it Matters

Achievement inequality matters because it heralds a lack of opportunities for the worst-off such that educational and economic progress across generations is hindered. It is well known that greater achievement is positively correlated with employability, better employment opportunities, and future earnings (Thernstrom & Thernstrom, 2003). Education that is interrupted or stalled, however, is much more likely than not to lead to poverty, and poverty is bound to lead to poor outcomes for children reared in it (Aber, Bennett, Conley, & Li, 1997; Duncan & Brooks-Gunn, 1997). Indeed, completing high school is one of three prerequisites to avoiding poverty. The other two, according to Senator Joe Lieberman, is to marry before having a child, and marry after the age of 20. “Seventy-nine percent of people who fail to do this,” says Lieberman, “are poor” (quoted in Browning, 2009, p. 85). This is sage advice as the literature on poverty has offered similar admonishments for at least a quarter of a century (Novak, 1987; Sawhill, 2003).

Achievement is also important to the degree that it correlates with parenting behaviors and the probability of single parenthood. Campbell and Parcel (2009) highlight the fact that the more highly educated mothers and fathers are, the stronger and more positive is the home environment and the greater the odds that children raised in such environments will progress through intellectual growth stages at a normal pace. Likewise, an intact family structure—wherein the biological mother and father are married and head the household together—is associated with a greater likelihood of economic advantage and lower rate of poverty relative to a broken family structure (McLanahan & Percheski, 2008). Lower incomes deriving from low education, broken family structure, or both, especially when coupled with inconsistent employment, serve

as stressors to parents. Typically exhibited as depressed self-confidence and increased anxiety with attendant mental health problems, these stressors lead ultimately to abusive parenting practices like screaming and hitting that are believed to harm children's development (Conger, Conger, & Elder, 1997).

To conclude, I should make clear what is meant by achievement. Often completed years of schooling alone yields little in the way of knowing the actual skills a person has accrued (Browning, 2009; Thernstrom & Thernstrom, 2003). Individuals with the same level of education, particularly when the education excludes status as a dropout, are sometimes unequally educated. "What matters," writes Browning (2009), "is the cognitive skills acquired in school, and that is very imperfectly indicated by how long one has spent in the classroom" (p.45). Completed years of schooling as a measure of achievement is therefore an imperfect predictor of productivity, and, hence, the likelihood of doing well in life. Valid and reliable standardized tests are the best way to capture differences in skill attainment, and, because of this, they serve as better predictors of life outcomes. This clarification is important with respect to the racial gap in achievement. If blacks are at a greater disadvantage relative to whites due to their lower educational attainment, which is partially responsible for their greater tendency toward early family formation, larger family size, less productivity on the job, and lower median age (the black median age in 2000 was 8 years younger than the white median age of 38), they are doubly cursed since Browning (2009) reports that they also fare poorer on standardized tests such as the Scholastic Aptitude Test (SAT; the black mean was 200 points lower than the mean score for whites) and the Armed Forces Qualification Test (AFQT; among 18 to 22 year olds in 1980, the black median score was 65 percent of the white median

score). These tests are themselves correlated with educational attainment and, therefore, those factors that it influences (Gottfredson, 1997; Plomin, 1994; Schmidt & Hunter, 2004). This clearly points to continued racial disparities in life outcomes heretofore unresolved by the various policies employed at various levels of government. That is, the intergenerational transmission of disadvantage will be a problem scholars will have to contend with for the foreseeable future if efforts are not made by scholars to be exacting in their treatment of what qualifies as educational achievement.

Focus of This Dissertation

The purpose of this dissertation is to investigate the ways in which the cognitive skills, or abilities, of parents, influence the academic and cognitive performance of their offspring. The prime motivating assumption is that parental skills, in addition to the well-known and widespread acceptance of them as operating via familiar social or environmental avenues such as early family formation or socioeconomic status (SES), are also embodied and, hence, to some degree heritable. At the intersection of these two pathways, I examine the conditions necessary for children's normal cognitive development and growth in three distinct yet related studies, focusing in particular on both proxy and psychometric measures of parental skill formation as the major predictor of child outcomes. Focusing on skill formation should go a long way in helping policymakers craft policies that can actually achieve the parity that has so long been the aim of social scientists.

Scholars like the Thernstroms and economist James Heckman (1998) believe that skill formation is paramount to closing the gap between the lowest and highest achievers.

They have argued, for instance, that where skills are disparate, earnings will reflect this. Equalize skills and earnings disparities are likely to disappear. Regarding psychometric measures of skill attainment specifically, work by Johnson and Neal (1998) confirms this claim. They found that, controlling for AFQT as a measure of productivity rather than controlling for educational attainment, the male black-white gap in wages was reduced by 75 percent and was entirely reversed for black females who actually earned more than their white peers with the same scores. The implication of increasing skills for one generation, at least as measured by direct measures of parental cognitive ability, is that the skills of the succeeding generation will also be improved over what they would have been in the absence of such increases. Often, though, parents occupy social locations that are indicative of low skill attainment, perhaps above and beyond that suggested by direct measures of ability. Either because of data limitations, imprecise operationalization of terminology, inadequate methods, or a number of other issues, however, these proxies for low skill attainment—e.g., early maternal age—have not been established as definitive predictors of child outcomes.

In the first essay, I explore the trajectories of mathematics and reading comprehension scores using a well-known nationally representative data set. Literature addressing the effects of early maternal age on children's outcomes has long reported the fact that young women who begin childbearing prior to age 20 are more likely to drop out of school (Furstenburg, Levine, & Brooks-Gunn, 1990), a state of affairs that has terrible consequences for the children of these early child-bearers (Coley & Chase-Lansdale, 1998). Also known, however, is the fact that it may be young mothers' own family backgrounds, and not their early maternal age per se, that is predictive of their proclivity

to drop out of school (Axinn, Duncan, & Thornton, 1997). To the extent that environmental risk tends to cluster (Amato & Keith, 1991), the tendency of children of the poor to engage early in sex and childbearing, to drop out of school, or both, suggests that both of these factors may be effective proxies for skill attainment over and above that officially measured.

On the effects of early maternal age on child outcomes, specifically, the literature to date has been mixed. The primary cause of this deadlock has mainly been methodological, but issues of early maternal age's differential impact across outcomes have plagued the literature as well. I make a unique contribution by utilizing growth curve modeling to highlight the individual nature of child development, focusing on how theories of the effect of early maternal age may differ across the life course. Whereas cross-sectional analyses and studies of incremental change are able only to assess aggregate-level effects, I emphasize the possibility that individuals can and often do deviate from the population curve. The importance of the results from this study is obvious. To the degree that children experience differential rates of learning, with the most disadvantaged—here defined as offspring of early child-bearers—struggling most and longest, and to the degree that differential rates differ across various outcomes, conventional programs to bridge the achievement gap in learning may be inadequate.

The second study explores the relationship between phenotypic maternal intelligence (as measured on the AFQT), SES, and children's performance on various psychometric measures of academic ability. Challenging the traditional approach of social science research on stratification, in which the relationship of SES to child development is considered a cause-effect one with little or no attention given to non-

environmental variables (Bankston & Caldas, 1998; Duncan & Brooks-Gunn, 1997; Taylor, Dearing, & McCartney, 2004), this essay incorporates research that explains parental SES as the result of the most salient of heritable traits, i.e., intelligence (Jensen, 1998; Neisser et al., 1996; Plomin, Defries, & Loehlin, 1977; Plomin, DeFries, McClearn, & Rutter, 1997). In mind is Herrnstein's syllogism (1971; Herrnstein & Murray, 1994), which states that, to the degree that social class is the result of cognitive abilities, believed to be largely heritable, social class is to some extent heritable as well.

In particular, I treat maternal intelligence as the proximal predictor of child outcomes and SES as a mediating factor, and seek to answer the question of whether the effect of mediation, when it exists, varies as a function of the level of maternal intelligence. Whereas much of the literature has tended to pit maternal intelligence against SES, this study attempts to highlight the way in which the two factors work together. Understanding whether and how the mediating effect of SES on the maternal intelligence-child outcomes relationship might be conditional on the levels of maternal intelligence could provide support to arguments favoring both in-kind transfers to vulnerable communities and the need for social capital development to make sure the impact of increased income is maximized.

The third essay of this dissertation examines how early childhood interventions of the kind offered in intense randomized trials might serve to close the racial and SES achievement gap. A social and economic case has been made for the broader implementation of preschool programs, with some scholars arguing for programs targeted at the most vulnerable and disadvantaged and others arguing for universal preschool (Cunha et al., 2006; Heckman, 2000, 2008; Heckman & Masterov, 2007;

Superintendent's Universal Preschool Task Force, 1998). Typically in these national policy debates, however, little thought is given to whether there is a limit, or an innate barrier, to how much intelligence can be raised. It is known, for instance, that many of the factors contributive to child outcomes—e.g., poverty status and the measure of the home environment—are themselves explained by phenotypic maternal IQ, a highly heritable trait (Plomin, 1994; Tymchuk & Andron, 1992).

Focusing on valid and reliable measures of maternal and child IQ (on instruments such as the Wechsler and Stanford-Binet scales), my goal in this essay is to elucidate whether there is treatment-effect heterogeneity by maternal IQ class. If children tend to be like their parents with respect to IQ, interventions to raise the IQs of the most vulnerable may have a ceiling. Currently unknown is where that ceiling is. As in the first essay, I utilize growth curve modeling in this study to understand how the treatment and control group children from the different maternal IQ classes perform over time. Explicating whether or not differences exist in the trajectories of children from different maternal IQ classes may help scholars determine if targeted or universal interventions provide the best model to deal with disparities in cognitive ability.

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CHAPTER 2

THE RELATIONSHIP BETWEEN EARLY MATERNAL AGE AND CHILDREN'S READING COMPREHENSION AND MATHEMATICS PERFORMANCE

Scholarship on the adverse effects of early maternal age on children's social, academic, behavioral, and health outcomes continues to be mixed. While some researchers find evidence in support of a direct causal effect on many outcomes such as school dropout, delinquency, internalizing and externalizing behaviors, and lower reading and mathematics scores during childhood and adolescence (Hardy et al., 1997; Hofferth, 1987; Hoffman & Maynard, 2008; Levine, Pollack, & Comfort, 2001), others find that the causal effects of early maternal age on child outcomes are difficult to establish, or are nonexistent (Hoffman, 1998; Rosenzweig & Wolpin, 1995). Those arguing for a causal connection most often highlight, of course, the direct effect of early maternal age on child outcomes, but also stress early maternal age's indirect impact on child outcomes via the stunted schooling, low income, and poor parenting skills of young mothers. That the children of mothers who began childbearing in the teen years fare poorly is due both to the fact of their mother's early maternal age and its effect on the health of the maternal household as characterized by the availability or unavailability of social capital-producing resources over the early life course. The literature refers to this argument as the *family circumstance* or *social influence hypothesis*.

Against these claims is the belief that risk derives not from early maternal age per se, nor even its mediated influence through the home environment, but from the previously unmeasured background factors (e.g., poverty, broken family structure) that select women into early sexual activity and teen childbearing, a possible source of bias. To the extent that a teen first birth has a statistically significant effect on child outcomes, whether directly or indirectly via the maternal household mediators, this effect is accounted for by young mothers' disadvantage during childhood and adolescence. The literature refers to this argument as the *selection hypothesis*.¹

Other recent research reveals the early maternal age-child outcomes relationship to be spurious, whether mediating factors, moderating factors, or both are considered (Geronimus, Korenman, & Hillemeier, 1994; Sullivan et al., 2011; Turley, 2003; Levine, Emery, & Pollack, 2007). That notwithstanding, others have shown that early maternal age remains strong and significant after controlling for the moderating factors of young mothers' family backgrounds and the mediating factors following their early first births (Jaffee et al., 2001; Jutte et al., 2010; Pogarsky, Lizotte, & Thornberry, 2003; Pogarsky, Thornberry, & Lizotte, 2006).

Why there are discrepancies in the empirical results of the effect of early maternal age on child outcomes should not be a mystery. It is likely the case that there are as many mechanisms or theories explaining the early maternal age-child outcomes relationship as there are outcomes to be studied. With respect specifically to issues of methodology, the extant literature has with few exceptions been limited to analyses of

¹ For greater clarity, I will refer to the *selection* and *family circumstance* or *social influence hypotheses* as the *maternal background* and *maternal household hypotheses*, respectively. The former relates to factors prior to and strongly predictive of young mothers' entry into sexual activity and early childbearing, while the latter focuses on those factors that are subsequent to the on-time transition to adulthood or post-first birth.

cross-sectional data, making it difficult to appreciate the consequences of early maternal age on outcomes in a developmental context. To be sure, the longitudinal analyses available are perhaps methodologically superior to the cross-sectional analyses, but they unfortunately offer little understanding of individual variability in intercepts, as well as the rates of change, for the specific outcomes often studied. Typical longitudinal analyses of change, which often focus on score changes in a two-wave design, are restricted to explicitly modeling aggregate-level growth curves, and thus fail to take into account that individuals vary in their rates of development (Gibbons et al., 1993). Explicitly modeling both aggregate-level and individual-level growth in child outcomes is advantageous over standard longitudinal analyses such as ANOVA because it allows for the exploration of rich hypotheses heretofore ignored (DeLucia & Pitts, 2006). The only study I have been able to find that attempts to understand the early maternal age impact in a growth curve context is one by Dahinten, Shapka, and Willms (2007), but the authors focus primarily on psychological and behavioral over academic outcomes. To the extent that they do focus on the latter, their predictors of interest are restricted to maternal household variables; maternal background factors are ignored.

Focusing on both the moderating effect of maternal background factors and the mediating influence of maternal household factors, the present study extends the current literature on the effects of early maternal age by employing individual growth curve analyses on two academic outcomes, the Peabody Individual Achievement Test (PIAT) for mathematics and for reading comprehension. The goal is to both sharpen theory for the two outcomes and to highlight the extent to which early maternal age directly or indirectly impacts children's growth in scores. The advantages of individual growth

curve analysis over the more traditional modeling of change as an incremental process is that it permits researchers (1) to test whether individuals vary from the population intercept in scores for a specific outcome, and, if so, (2) to then assess whether that variability might be predicted from maternal background and maternal household factors. Growth curve analysis also allows for greater appreciation for the possibility that early maternal age, net of other factors, may be predictive of scores at initial status only but not of growth in scores, or of growth in scores only but not of scores at initial status. Finally, in cases where there remains, after controlling for maternal background and maternal household factors, a statistically significant effect of early maternal age on the growth in scores, it is possible in a latent variable model to examine whether the convergence or divergence in scores is due to processes set in motion prior to the commencement of formal education—perhaps owing to differences in mother’s age at first birth, among other things—or is primarily a result of the schooling experience (Raudenbush & Bryk, 2002).

BACKGROUND

The Direct and Indirect Effects of Early Maternal Age

Compared to their peers born to mothers who delay childbearing until after adolescence, children born to teen mothers are at increased risk for a whole host of poor outcomes (Corcoran, 1998; see edited volume by Maynard, 1997). Spieker et al. (1999) found that preschool and school-age children of teen mothers had a higher rate of behavior problems than children of non-teen mothers, while Furstenberg, Brooks-Gunn, & Morgan (1987) found that adolescents had a higher risk of school dropout and delinquency. Early

maternal age also adversely impacts children's performance on academic tests (Moore, Morrison, & Greene, 1997). Females born to teen mothers have an elevated likelihood for teen pregnancy and childbearing, thus likely guaranteeing the transmission of disadvantage to future generations (Botting, Rosato, & Wood, 1998; McLanahan & Sandefur, 1994). Differences in outcomes by maternal age, across the broad spectrum of outcome measures, persist and even widen as children move from childhood into the teen years (Brooks-Gunn & Furstenberg, 1986). Interestingly, the children of mothers who begin childbearing in the teen years, who are themselves born after their mothers leave adolescence, also bear increased risk for suboptimal outcomes compared to later-born children of mothers who begin childbearing after adolescence (Jutte et al., 2010; Nagin & Tremblay, 2001).

At least part of the reason for the association between early maternal age and children's outcomes may be explained theoretically by the life course framework, particularly its emphasis on age-specific expectations or "on-time transitions," and the inability of some, perhaps due to circumstances outside their control, to meet them (Neugarten, Moore, & Lowe, 1965). Childbearing, which ideally should occur in adulthood, and preferably after formal schooling and marriage, has long-term negative consequences when achieved in the teen years, both for young mothers and for the children born to them. A birth in the teen years is likely to disrupt young women's completion of education (Furstenberg, Levine, & Brooks-Gunn, 1990), which, in turn, is associated with penury and its concomitant social disadvantage in adulthood (Coley & Chase-Lansdale, 1998; Hotz, McElroy, & Sanders, 1997). Early child-bearers are also more likely to raise a child without the support of the child's father, which, according to

research, is detrimental to the educational attainment of the children of these women (Astone, 1993).²

The combined impact of retarded maternal education, low socioeconomic status, and single parenthood with no supplemental social support structure on children's development is mediated still at another level, that of parenting style. Young mothers are more inclined than older mothers toward severity in the disciplining of their children (Berlin, Brady-Smith, & Brooks-Gunn, 2002). Because they have few or no resources on which to draw during the childrearing years, young women oftentimes end up as the heads of homes characterized, in particular, by the lack of fixed routines or regularities, high noise levels, and disparate people coming and going, i.e., general disorganization. As Wachs (2005) has made clear, the organization of the household is proximally linked with the quality of the parenting children receive. Also, a household setup wherein financial and social resources are limited very often engenders harsh parenting practices since young mothers may be ill equipped to handle the inexorable demands of childrearing (Scaramella & Conger, 2003). This affects children in a profound way. Children who are consistently the target of harsh or abusive parenting strategies often do not receive any positive and nurturing support from their parents, which impacts not only their long-term relationships with those parents, but also their relationship with those outside the home (Granic & Patterson, 2006). Because they have been socialized, vis-à-vis their parents' harsh parenting style, to employ anger and aggression in the resolution of conflicts, these children tend to drive out of their lives positive peer relationships, and

² In a Bureau of Labor Statistics report by Jeff Grogger and Nick Ronan (1995), fatherlessness was not as consequential for blacks after controlling for family-specific unobservables. In fact, blacks raised in single parent households actually acquired more education than they would have if both parents were present in the home. Whites and Hispanics, on the other hand, suffered with respect to educational attainment when fathers were absent.

they ultimately end up allying themselves with others who share their antisocial disposition (Simons et al., 1996). This only reinforces bad behavior and forestalls the normative declines in externalizing behaviors that should occur in later childhood (Gilliom & Shaw, 2004).

In summary, children of mothers who begin their childbearing early are at increased risk for certain adverse outcomes because their mothers are lacking in the social and human capital needed for success in a postindustrial market economy. Because of family circumstances deriving from their mothers' early maternal age, which interrupts the expected order of the life course and leads to educational underachievement, lower income, poor parenting practices, and suboptimal parent-child interactions, the children of these women begin life with a great disadvantage compared to their peers born to mothers who delayed childbearing until after the teen years.

Maternal Background Confounders of the Early Maternal Age Effect

The foregoing empirical evidence notwithstanding, there remains a lack of consensus about whether the link between adolescent first birth and children's later outcomes is causal. Failing to account for the background characteristics of young mothers, it is argued, necessarily leads to an overestimation of the real effect of early maternal age on children's outcomes (Bronars & Grogger, 1994). The most obvious background factor that might explain the early maternal age-child outcomes relationship is family income. If, as was highlighted above, lower family income and its correlates are associated with a greater risk for teen pregnancy, it must explain at least some, if not all, of the intergenerational similarity in outcomes among mothers who began childbearing early

and their offspring. The economic resources of young mothers' families are significantly correlated, for instance, just as is early maternal age, with their likelihood of school completion (Axinn, Duncan, & Thornton, 1997). Females who grow up in poor households are more likely than their peers who grow up in non-poor households to drop out of formal schooling. When poverty is concentrated at the neighborhood level, there is also an increased probability of being retained in grade, a factor that might lead children reared in poor communities to perceive, rightly or wrongly, that educational attainment is not worth the effort (Guevremont, Roos, & Brownell, 2007).

Other indirect effects of constrained family economic resources on young women's propensity toward early initiation of sexual activity and childbearing occur via broken family structure, harsh parenting, and lack of an adequate learning environment, among other things. Indeed, because social environmental risks tend to cluster and are not randomly distributed throughout the population (Amato & Keith, 1991), where one risk is present in a child's life, its correlates are likely to coexist alongside it. Children raised in poverty, for instance, are more likely not only to engage early in sex and childbearing or to encounter difficulty with formal schooling, but they are also more likely to be the targets of abusive parenting and to live in nonexpectable environments, where positive parent-child interactions are few or nonexistent. To be sure, the line drawn from these disadvantages in a young mother's past to lower future income and its attendant low social status is not unexpected. And if such past disadvantage is a detriment for young mothers, it is much more so for their children.

The important question that has yet to be definitively answered is whether the direct effect on children's outcomes of an early first birth ceases to be statistically

significant after controlling for maternal background factors. Some scholars have found the effect of early maternal age on mediating factors such as the home environment (Geronimus et al., 1994) and on children's fertility timing (Barber, 2001) to disappear after controlling for mothers' family background characteristics. Comparing the outcomes of sisters who had first births at different ages, Geronimus & Korenman (1992) showed that, while the early child-bearers were less likely to have had any postsecondary education than their postponing sisters, they did about as well on economic measures throughout their late 20s and into their early 30s. That sisters share a common background but show no real difference in their socioeconomic status in adulthood suggested that the mediating pathway from an early first birth to maternal household factors such as family income to children's outcomes must be explained by the backgrounds from which mothers come. This is what later evidence appeared to confirm when Geronimus et al. (1994) compared various outcomes among first cousins, one set born to the sister who began childbearing early and the other set born to the sister who postponed childbearing.³ While these family fixed effects studies revealed that there was no statistically significant negative effect of a teen first birth on verbal memory, behavior problems, or reading recognition scores after controlling for young mothers' family background and current socioeconomic status, the null hypothesis of no difference was rejected with respect to picture vocabulary, mathematics, and reading comprehension scores, and the coefficients for these outcomes, interestingly, favored the children born to early child-bearers. Because the Geronimus et al. (1994) data was drawn from what is now referred to as the National Longitudinal Study of Youth, Children and Young Adults

³ In the case of families where more than two sisters were represented, the authors weighted the data so that each family of origin contributed the equivalent of one pair of mothers.

(NLSY-CYA), which began administering cognitive and behavioral assessments biennially in 1986, the sample size in 1994 was limited, and, thus, so were the generalizability of the results.

Taking advantage of four additional rounds of data, and thereby increasing the sample size, Turley's (2003) replication of the Geronimus et al. (1994) study confirmed (1) once family background factors were controlled, the cousins born to the older mothers did not perform significantly better on achievement measures than did their cousins born to younger mothers, and (2) even before controlling for family background factors, there was no difference in the trajectory of the cousins' scores. Turley (2003) concluded that the negative association observed between early maternal age and child outcomes primarily reflects young mothers' origins (i.e., family structure, family income, etc.) and not early childbearing per se, nor its accompanying indirect effects via the home environment, parenting skills, or income. Research by Brien, Loya, & Pepper (2002) and Levine et al. (2001) appear to buttress this claim. Levine et al. (2007) found, though, that while an early maternal age plays no causal role in young children's test scores, it does have a direct effect on the propensity toward behavioral problems and on the likelihood of grade repetition.

Problematic with both Geronimus et al.'s (1994) and Turley's (2003) studies, however, and with cousin comparisons or family fixed effects models, generally, is the muted assumption that the cousins' mothers (i.e., sisters) are more alike than they are dissimilar. Choosing fixed effects models over explicit control models may alleviate concerns over omitted variables bias, but such models pose their own shortcomings in that they can only control for those background traits that sisters share. The unobserved

differences between sisters that could affect their fertility are ignored. It is interesting to note that Geronimus et al. (1994) found that early child-bearers had slightly lower scores on the Armed Forces Qualification Test (AFQT) than their sisters who postponed childbearing. AFQT differences are associated with early initiation of sexual activity and other delinquent behaviors that may have adverse effects on the life chances of children (Fergusson & Horwood, 1995). To the degree that such differences are statistically significant, the predictive power of maternal background factors may be weakened.

To be sure, even after controlling for many previously unobserved background characteristics, some researchers have found that early maternal age, although reduced in its effect, continued to exert a significant impact on many, though not all, outcomes (Goodman, Kaplan, & Walker, 2004; Klepinger, Lundberg, & Plotnick, 1999). Jaffee et al. (2001), testing the effects of an early first birth on outcomes such as early school leaving, unemployment, and violent offending, found that only 39% of the early first birth effect was accounted for when controlling for both young mothers' background or selection factors and present household factors. In their analysis of Rochester Youth Development Study data, Pogarsky et al. (2006) found that the mediating factors of the maternal household only accounted for just less than 30% of the early first birth effect on some of the same outcomes of interest in the Jaffee et al. (2001) study. The results of the Pogarsky et al. (2006) study were striking in that the data used were primarily based on information culled from minorities; eighty-five percent of the 1000 subjects in the study were either Black or Hispanic, and only 15% were white. It has been suggested by previous research that early childbearing among minority communities may be more normative, and thus less of a risk for their long-term behavioral and academic outcomes

(Burton, 1990). That there were statistically significant negative effects of an early first birth on the various outcomes analyzed suggests that that hypothesis may be overstated.

The lack of agreement on what, if anything, explains the early childbearing-child outcomes relationship suggests there may be multiple mechanisms or theories at play, and that each may be relevant to specific outcomes while failing to account for others. It is likely also the case that the various methodologies heretofore used to study the consequences of early maternal age for children's life chances, both cross-sectional and longitudinal, are inadequate to the task. Cross-sectional analyses, while they may reveal differences at a given point in time, reveal little understanding of the developmental nature of many of the outcomes studied. To address the shortcomings of cross-sectional analyses, and to focus on change, many of the researchers I have highlighted above have made use of longitudinal analyses, but Raudenbush & Bryk (2002, pp. 160-161) have identified a number of issues that have plagued typical studies of change. Regarding conceptualization, measurement, and design, researchers, they argue, have been largely misguided in their uses of longitudinal data to study change. For instance, it is a basic principle of developmental theory that individuals vary in their rates of development (DeLucia & Pitts, 2006), but until recently little research on change existed that conceptualized an explicit model of individual growth. The focus has instead been on aggregate-level, or population, growth only. With respect to measurement issues, to the degree that studies of change utilize instruments originally developed to differentiate among individuals at a fixed time point, such measures may be unable to extricate how individuals differ in their rates of change. Again, much of the analytic results may be limited to population-level growth curves. Most important, however, has been the

problem of design. Raudenbush and Bryk (2002) emphasize the point that, because the statistical precision of longitudinal studies is affected by both their frequency and duration, the two-wave designs used in studies of change are simply inadequate for studying individual growth.

Individual growth curve models, an outgrowth of hierarchical linear modeling (HLM), afford researchers the opportunity to study change over time for outcomes of interest at the aggregate- and individual-levels (DeLucia & Pitts, 2006). This technique represents an advantage over methods used in the past, foremost among them the ability to ascertain the extent to which theoretically meaningful variables, in this case those related to maternal background and maternal household factors, contribute to individual deviations from the aggregate-level, or population, curve. Individual growth curve models also allow for the treatment of the time variable as continuous rather than as incremental (Bryk & Raudenbush, 1992; Gibbons et al., 1993). Also, because individual growth curve models are so flexible, it is not necessary that all individuals be measured at each occasion.

Despite the advantages of individual growth curve modeling for studying change, as well as the length of time both data and software have been available to carry out HLM analyses, the only study I have been able to find that examines the impact of early maternal age on children's, or more accurately adolescents' (children between 10 and 15 years of age), outcomes is an analysis of Canadian data by Dahinten et al. (2007). While the authors focus primarily on psychological and behavioral outcomes, they do include one academic outcome, mathematics score, which at least gives a sense of how an early first birth impacts the initial status and trajectory of scores. After accounting for maternal

household factors such as income and maternal education, as well as controlling for maternal depression and parenting behaviors, the authors found a statistically significant effect of an early first birth—i.e., a birth between the ages of 13 and 17—on mathematics score at age 10, the initial status in their study. Early maternal age was not, however, related to the linear slope in mathematics scores. Whether additional controls for maternal background factors might have changed the relationship between early maternal age and either initial status or the linear slope remains unclear.

THE PRESENT STUDY

The present study extends the current literature by using matched data from the National Longitudinal Study of Youth, 1979 (NLSY79) and the National Longitudinal Study of Youth, 1979 – Children and Young Adults (NLSY79-CYA) to examine how, using individual growth curve modeling, children’s trajectories on the Peabody Individual Achievement Test (PIAT) for mathematics and for reading comprehension are influenced by early maternal age prior to and after controlling for both maternal background and maternal household factors. That the literature remains mixed on the statistical significance of an early first birth makes it difficult to formulate informed hypotheses for specific outcomes. It is possible, however, to assume from most of the available research that early maternal age will be associated with lower mathematics and reading comprehension performance before accounting for maternal background and maternal household factors. I expect this effect to be true for both initial status and for the rate of change in scores. It is also safe to hypothesize both a moderating impact of maternal background factors and a mediating impact of maternal household factors, though the

strength of the moderating and mediating influence may differ between the two outcomes.

I do offer the following proviso with respect to the foregoing hypotheses. Given the effects of a teen first birth on those mediating factors that adversely impact the maternal household, it is apparent why there might be divergent initial reading comprehension scores between children born to mothers who began childbearing in adolescence and those who delayed childbearing until after the teen years. To the degree that educational attainment is stunted or interrupted due to a woman's early maternal age, her children will suffer directly the consequence of lowered verbal, and thus reading, achievement. It has indeed been empirically shown that if, after the birth of their children, women continue their previously interrupted education, on average their children's performance on measures of reading achievement improve (Magnuson, 2007). The results for the influence of increases to mother's educational attainment on children's mathematics skills revealed no such improvement, a detail that may be explained by the fact that mathematics instruction is learned primarily via formal instruction (Entwisle & Alexander, 1992). An important question is whether the mean initial mathematics score would be as sensitive to, say, socioeconomic status as reading achievement is expected to be.

Whatever the agreement or differential effect of an early maternal age on the initial status of mathematics and reading comprehension, a final important question that needs answering is whether the scores of children born to the two sets of mothers (early starters and delayers) diverge over time and whether this divergence can be attributed to factors prior to formal schooling or is a direct effect of the schooling experience.

METHODS

Sample

To examine empirically the hypotheses put forward, I analyze data from the National Longitudinal Survey of Youth, 1979 – Children and Young Adults (NLSY79-CYA). The respondents in the NLSY79-CYA are the biological offspring of the female respondents of the National Longitudinal Survey of Youth, 1979 (NLSY79), a nationally representative sample of 12686 adolescents and young adults who were aged 14 through 22 at the NLSY79's initiation in 1979. With the accumulation of time, and the attendant growth in family size among NLSY79 women, the weighted mother-child data, excluding women who were in the military or who were part of the economically disadvantaged white oversample ($N = 1352$ out of 6283 total NLSY79 women) are representative of a cross-section of women who were between 14 and 22 in 1979. Biennially, from 1986 to 2006, NLSY79-CYA respondents were asked survey questions similar to those asked of their mothers. While many questions touched on topics relating to employment, schooling, interactions with parents and peers, dating habits, and delinquent behavior, respondents also had administered to them, when they met the requisite developmental standards, several cognitive assessments. This paper focuses on two of those assessments.

Dependent Measures

The outcome measures were percentile scores on the mathematics and reading comprehension portions of the Peabody Individual Achievement Test (PIAT), which was administered to NLSY79-CYA children who were PPVT-AGE 5 through 14 in the even-

numbered years from 1986 to 2006.⁴ The PIAT reading comprehension consists of 66 sentence items of increasing difficulty in which a child chooses from an array of pictures the one that best represents a sentence's meaning. The PIAT mathematics consists of 84 multiple choice questions—also of increasing difficulty—which assess children's ability to, at the most basic level, recognize numbers, and to, at a more advanced level, handle trigonometric concepts.

The sample drawn for each outcome included the total number of person-years for which NLSY79-CYA staff published a valid score. Because the PIAT reading comprehension scores were not standardized for 5 and 6 year olds, analysis began at PPVT-7 years of age for this outcome. Excluding those either too old to take the test, those not yet age-eligible, or those with nonstandard scores, then, the PIAT mathematics yielded 9047 respondents and the PIAT reading comprehension 8339 respondents. Of those contributing mathematics percentile scores, 993 had one score, 1251 had two scores, 1429 had three scores, 2679 had four scores, and 2695 had five scores. The total number of mathematics scores available for analysis, then, was 31973. Of those contributing reading comprehension percentile scores, 1143 had only one score, 1594 had two scores, 2688 had three scores, and 2914 had four scores. A total of 24051 valid person-year reading comprehension scores were available for analysis.

⁴ The PPVT refers to the Peabody Picture and Vocabulary Test and is a measure of verbal intelligence. Since it may be converted to *mental age*, a person's score on the PPVT measure is an indicator of extent of cognitive development, and, as such, it serves as a control for deficiencies that may suggest impaired or retarded functioning. NLSY staff, therefore, advocates the use of PPVT-age over chronological age when examining measures of the Peabody scales.

Independent and Control Measures

Early maternal age, my primary predictor of interest in this study, has often been treated differently in the existing literature, with some researchers focusing on those who began childbearing before the age of 20 and others additionally distinguishing between early (i.e., prior to age 17 or 18) and late (i.e., after age 17 or 18) teen child-bearers on the assumption that there may be differences between these two teen groups. As I think it is the more conservative approach, I have chosen to adhere to the former analytic strategy, dichotomizing the variable referencing age at first birth such that 0 denoted post-adolescent entry (i.e., after age 19) into childbearing, and 1 denoted an adolescent first birth (i.e., before age 20). Since research shows that the outcomes of children born to teen mothers and the later born children of mothers who had a first birth in the teen years do not differ significantly, I do not control for whether within family births differ across the dichotomized early maternal age variable, and instead assume the effect of an early first birth has the same impact on initial scores and growth trajectories for all children born to the same mother.

Maternal Background Factors

The maternal background factors included as controls were race—dichotomized to distinguish between Black and Hispanic females (coded 1) and all others, who were predominantly white (coded 0)—number of siblings in the household at age 14, and whether the family resided in the south at age 14. An index of socioeconomic status was created by standardizing the sum of the z-transformed values of (1) the natural log of net family income plus 1 in the year prior to NLSY79 study inception, (2) the highest grade

of both parents at NLSY79 study inception, and (3) the maximum Duncan Socioeconomic Index value of the young girls' mother and father when the girls were 14. The reliability of the four-item scale, as measured by Cronbach's alpha, was about .75 for both the mathematics and reading comprehension data sets, suggesting the various items are measuring the same underlying construct.

Kessler et al. (1997) found that young women who enter motherhood prematurely tended to have a long history of conduct disorder, including aggression, and Woodward & Fergusson (1999) have highlighted the fact that a history of aggression is proximally related to an increased risk for early childbearing. To the degree that teen pregnancy and early maternal age are simply illustrative examples of an entire universe of problem behaviors in which some young women engage, from premarital sex to alliances with antisocial peer groups to illicit drug use (Miller-Johnson et al., 1999; Pogarsky et al., 2003), their effects on children's outcomes should, to some extent, be accounted for by such behavior. Therefore, in considering the degree to which early maternal age effects on children's mathematics and reading comprehension scores are explained by maternal background factors, I also focus on those factors that denote women's aggressive and antisocial behaviors prior to beginning childbearing.

In 1980, the NLSY79 gathered information from respondents on their delinquent behaviors in the previous year. Originally entered on an ordinal scale from 0 (NEVER) to 6 (MORE THAN 50 TIMES), the relevant items asked, for example, the number of times in the past year a respondent (1) "purposely damaged property that did not belong to you?," (2) "gotten into a physical fight at school or work?," (3) "used force or strong arm methods to get money or things from a person?," (4) "hit or seriously threatened to

hit someone?,” (5) “attacked someone with the idea of seriously hurting or killing them?,” or (6) “used any drugs or chemicals to get high or for kicks, except marijuana?” For purposes of the current study, I have constructed from 18 of 21 items a scale of delinquent behavior at NLSY79 study inception.⁵ Each item was standardized, and then all of the z-transformed items were summed before being standardized again. The scale reliability coefficient, or Cronbach’s alpha, was about .79 for both the mathematics and reading comprehension data sets.

Finally, I also entered as a maternal background control young women’s scores on the Armed Forces Qualification Test (AFQT)—a test of cognitive ability or aptitude that is drawn from the arithmetic reasoning, word knowledge, paragraph comprehension, and numerical operations portion of the Armed Services Vocational Aptitude Battery (ASVAB; National Longitudinal Surveys, 1999), and which is highly correlated with formal tests yielding an intelligence quotient (IQ). Maternal cognitive ability has been shown to have a strong association with many long-term outcomes for children, often accounting fully for the effect of factors such as socioeconomic status, children’s home environments, the absence of adequate learning opportunities, and low maternal education, things that have long been held to be proximal predictors of children’s cognitive and behavioral development (Mayer, 1997; Plomin, 1994; Tymchuk & Andron, 1992). Maternal AFQT was centered such that the intercepts for initial status and the age factors reflected the average score or growth in scores at the mean maternal AFQT value.

⁵ The excluded delinquency items were (1) number of times ran away in past year, (2) number of times skipped school in past year, and (3) number of times drank alcohol in past year. Their exclusion from the bevy of other delinquency variables available, which often focused on much riskier behavior, led to a higher reliability estimate of the created measure; hence, their absence from final analysis.

Child-Specific and Maternal Household Factors

The child-specific variables entered as controls were sex (female coded 0, male coded 1), gestational age, measured in weeks, and birth weight, measured in ounces. For the mathematics and reading comprehension data sets, these latter two variables were centered at the grand mean.

For each respondent's first reported score, the grand mean-centered values for the natural log of net family income plus 1 and mother's highest grade were also included as controls. While values on these variables vary across time in the real world, I restrict my analysis to treating them as time-invariant, primarily for methodological reasons. Since part of my analysis involves the use of latent variable regression to assess the causes explaining growth trajectories, and because I wish to control for the full bevy of maternal background and maternal household factors as they relate to initial status and age, treating family income and mother's highest grade as time-invariant is optimal.⁶

Data Analysis Plan

Missing values of the independent variables were handled via multivariate imputation by fully conditional specification (Lee & Carlin, 2010; Raghunathan et al., 2001; Van Buuren et al., 2006) using SPSS Statistics 19.0. It is debated what the optimal number of imputations is to arrive at efficient estimates. Schafer and Olsen (1998) and Rubin (1987) suggest no more than 3-5 imputations as the gains to efficiency tend diminish after

⁶ Regarding the initial HLM models that are the foundation of my analysis, I did compare the output of models in which some of the maternal household variables were treated as time-varying, controlling for the same at baseline of course, with those in which the maternal household variables were treated as time-invariant—i.e., included at baseline, or initial status, but also inserted into the level-two equations for age and, in the case of the mathematics data, age²—and found that there was little difference in the mediating effect on early maternal age.

this point. In a recent article by Graham, Olchowski, & Gilreath (2007), however, it is argued that many more imputations should be used than previously advocated, perhaps 20 or more. Choosing the middle path, I created 10 multiply imputed data sets, and then made use of HLM 6.0 to carry out a growth curve analyses on children's PIAT mathematics and reading comprehension performance. One of the advantages of HLM software is its ability to produce a single estimate for each multiply imputed data set and to average over them to arrive at a final set of coefficients. Additionally, whereas most statistical software requires a great amount of time to execute the computations of growth curve modeling, HLM is not limited by such constraints and is relatively swift.

The hierarchical linear model was specified such that, at level one, individual growth in mathematics and reading comprehension scores were related to age. Level two examined whether these parameters varied across individuals by early maternal age, maternal background factors, and maternal household factors. While Raudenbush and Bryk (2002) advocate a linear growth model when the number of assessment occasions per individual is few, I nevertheless tested whether either of the outcomes of interest here showed a nonlinear growth trajectory. Only the mathematics data revealed the need to include a quadratic term to improve model fit. Reading comprehension growth, on the other hand, was fairly linear. The unconditional growth model representing mathematics and reading comprehension scores are represented, each in its turn, in the level one models specified below:

$$\text{Score}_{ti} = \pi_{0i} + \pi_{1i}(\text{age})_{ti} + \pi_{2i}(\text{age}^2)_{ti} + e_{ti}, \quad (2.1)$$

$$\text{Score}_{ti} = \pi_{0i} + \pi_{1i}(\text{age})_{ti} + e_{ti}. \quad (2.2)$$

The level two model was specified as:

$$\begin{aligned}
 \pi_{0i} &= \beta_{00} + r_{0i} \\
 \pi_{1i} &= \beta_{10} + r_{1i} \\
 \pi_{2i} &= \beta_{20} + r_{2i} \text{ (mathematics model only)}
 \end{aligned}
 \tag{2.3}$$

Children's performance on the PIAT mathematics and reading comprehension assessments were measured at time t for the i th individual in the sample. The metric for age, centered at PPVT-age 5, represents the mean expected growth rate from age 5 on.⁷ The parameter, π_{0i} , then, represents the initial score at PPVT-age 5. The level-two beta coefficients were expected to reveal that mean initial scores (β_{00}), mean growth in scores (β_{10}), and, for the mathematics data, mean acceleration or deceleration in the growth in scores (β_{20}) differ across individuals. That is, the children were allowed to differ from the aggregate- or population-level intercepts.

Following my unconditional models, I then estimated the degree to which early maternal age conditioned the intercept, the slope of age, and in the case of the mathematics assessment, the slope of the quadratic term, age^2 . An example of the resultant model is shown for the reading comprehension data.

$$\begin{aligned}
 \pi_{0i} &= \beta_{00} + \beta_{01}(\text{adolescent first birth})_i + r_{0i} \\
 \pi_{1i} &= \beta_{10} + \beta_{11}(\text{adolescent first birth})_i + r_{1i}
 \end{aligned}
 \tag{2.4}$$

⁷ REMINDER: Due to the absence of non-standard scores for 5 and 6 year olds, the age metric for the PIAT reading comprehension is set to reflect the mean expected growth rate from age 7 on.

Consistent with previous research on the effects of early maternal age on children's cognitive development, early maternal age was expected to be significantly and negatively related to initial status, and to the linear and nonlinear factors.

A third model extended the model represented in equation 2.4 by adding to level-two the maternal background factors. Again, using the reading comprehension data, the resulting equation is represented thusly:

$$\begin{aligned}\pi_{0i} = & \beta_{00} + \beta_{01}(\text{adolescent first birth})_i + \beta_{02}(\text{MBsocioeconomic index})_i \\ & + \beta_{03}(\text{MBBlack or Hispanic})_i + \beta_{04}(\text{MBnumber of siblings})_i \\ & + \beta_{05}(\text{MBresided in south})_i + \beta_{06}(\text{MBdelinquency})_i + \beta_{07}(\text{MBAFQT})_i + r_{0i}\end{aligned}$$

$$\begin{aligned}\pi_{1i} = & \beta_{10} + \beta_{11}(\text{adolescent first birth})_i + \beta_{12}(\text{MBsocioeconomic index})_i \\ & + \beta_{13}(\text{MBBlack or Hispanic})_i + \beta_{14}(\text{MBnumber of siblings})_i \\ & + \beta_{15}(\text{MBresided in south})_i + \beta_{16}(\text{MBdelinquency})_i + \beta_{17}(\text{MBAFQT})_i + r_{1i} \quad (2.5)\end{aligned}$$

In a final conditional model, I estimated the effects of both the maternal background and the child-specific and maternal household factors on the intercept, rate of growth, and, again, in the case of the mathematics data, the rate of acceleration or deceleration. Using the mathematics data as an example, here is how the level-one growth equation was specified for model 4:

$$\text{Score}_{\bar{u}} = \pi_{0i} + \pi_{1i}(\text{age})_{ti} + \pi_{2i}(\text{age}^2)_{ti} + e_{ti}. \quad (2.6)$$

The level-two model was specified as:

$$\begin{aligned}\pi_{0i} = & \beta_{00} + \beta_{01}(\text{adolescent first birth})_i + \beta_{02}(\text{MBsocioeconomic index})_i \\ & + \beta_{03}(\text{MBBlack or Hispanic})_i + \beta_{04}(\text{MBnumber of siblings})_i \\ & + \beta_{05}(\text{MBresided in south})_i + \beta_{06}(\text{MBdelinquency})_i + \beta_{07}(\text{MBAFQT})_i \\ & + \beta_{08}(\text{MHmale})_i + \beta_{09}(\text{MHgestation})_i + \beta_{010}(\text{MHbirth weight})_i \\ & + \beta_{011}(\text{MHnet family income})_i + \beta_{012}(\text{MHmother's highest grade})_i + r_{0i},\end{aligned}$$

$$\begin{aligned}\pi_{1i} = & \beta_{10} + \beta_{11}(\text{adolescent first birth})_i + \beta_{12}(\text{MBsocioeconomic index})_i \\ & + \beta_{13}(\text{MBBlack or Hispanic})_i + \beta_{14}(\text{MBnumber of siblings})_i \\ & + \beta_{15}(\text{MBresided in south})_i + \beta_{16}(\text{MBdelinquency})_i + \beta_{17}(\text{MBAFQT})_i \\ & + \beta_{18}(\text{MHmale})_i + \beta_{19}(\text{MHgestation})_i + \beta_{110}(\text{MHbirth weight})_i \\ & + \beta_{111}(\text{MHnet family income})_i + \beta_{112}(\text{MHmother's highest grade})_i + r_{1i},\end{aligned}$$

$$\begin{aligned}\pi_{2i} = & \beta_{20} + \beta_{21}(\text{adolescent first birth})_i + \beta_{22}(\text{MBsocioeconomic index})_i \\ & + \beta_{23}(\text{MBBlack or Hispanic})_i + \beta_{24}(\text{MBnumber of siblings})_i \\ & + \beta_{25}(\text{MBresided in south})_i + \beta_{26}(\text{MBdelinquency})_i + \beta_{27}(\text{MBAFQT})_i \\ & + \beta_{28}(\text{MHmale})_i + \beta_{29}(\text{MHgestation})_i + \beta_{210}(\text{MHbirth weight})_i \\ & + \beta_{211}(\text{MHnet family income})_i + \beta_{212}(\text{MHmother's highest grade})_i + r_{2i} \quad (2.7)\end{aligned}$$

All of the models included random intercepts, random slopes in age and age², and intercept-slope covariance at the child level to allow for the association between measures. Full maximum likelihood estimation was used for all models.

Finally, given an association between early maternal age and initial status, and between early maternal age and rate of growth, I tested whether the convergence or divergence in scores over time was attributable to either (1) the early maternal age differences at initial status, or (2) the schooling experience. Following the example of Raudenbush & Bryk (2002), I formulated a model for the latent growth rate as a function of early maternal age, maternal background and household factors, and the latent initial status:

$$\begin{aligned}
\pi_{1i} = & \alpha_{10} + \alpha_{11}(\text{adolescent first birth})_i + \alpha_{12}(\text{MBsocioeconomic index})_i \\
& + \alpha_{13}(\text{MBBlack or Hispanic})_i + \alpha_{14}(\text{MBnumber of siblings})_i \\
& + \alpha_{15}(\text{MBresided in south})_i + \alpha_{16}(\text{MBdelinquency})_i + \alpha_{17}(\text{MBAFQT})_i \\
& + \alpha_{18}(\text{MHmale})_i + \alpha_{19}(\text{MHgestational})_i + \alpha_{110}(\text{MHbirth weight})_i \\
& + \alpha_{111}(\text{MHnet family income})_i + \alpha_{112}(\text{MHmother's highest grade})_i \\
& + \alpha_{113} \times \pi_{0i} + u^*_{1i}
\end{aligned} \tag{2.8}$$

If the association between early maternal age and the rate of growth is fully explained by the differential impact of early maternal age at initial status, i.e., if there is no direct effect of α_{11} in the latent growth model, then growth may be argued to be primarily a result of processes set in motion prior to entry into formal schooling. Alternatively, a significant direct effect of the early maternal age coefficient in the latent model would suggest that the schooling experience also contributes to the divergence or convergence in test scores.

RESULTS

Descriptive Statistics

Table 2.1 compares, for both the mathematics and reading comprehension samples, the means and standard deviations of the maternal background and household factors of women who had a teen first birth to those who postponed childbearing. Of the 4009 mothers in the mathematics sample and the 3781 mothers in the reading comprehension sample, 1452 and 1402 women, respectively, had an early maternal age. These women came from backgrounds that were, on average, more disadvantaged than the backgrounds of their peers who postponed childbearing, and they also headed households that tended to perpetuate this disadvantage to the next generation. Compared to the parents of adult child-bearers, the parents of early child-bearers had lower levels of educational attainment, worked in careers that were less prestigious, and earned 40% less in income. The differences in family background by maternal age status were consistent across the generations as early child-bearers, not unlike their parents, had lower levels of educational attainment and less than half the income than their postponing peers. Not surprising is the fact that minorities such as Blacks and Hispanics were more likely than Whites to have an early first birth. An early first birth was also associated with larger sibship size, southern residence, and depressed cognitive ability. Indeed, statistically significant differences in means were found for all factors except for young women's level of delinquency during adolescence and the gestational age of the women's children.

Mathematics Growth

Table 2.2 shows the results of the hierarchical linear growth model for mathematics achievement. In agreement with research produced by Dahinten et al. (2006), the random effects parameters shown under Model 1 reveal that a quadratic shape was the best fit for the mathematics data. That is, there is significant variation in individual scores at PPVT-age 5 and across age, allowing for nonlinearity. Model 2 supported the available research on the effects of early maternal age in the absence of controls. Regarding the data used here, early maternal age was related to initial mathematics percentile score, age, and age². On average, children born to women who began childbearing prior to age 20 scored, at PPVT-age 5, about 11 percentile points below their peers born to adult child-bearers. Additionally, while all children gained with respect to mathematics performance, children of early child-bearers did so at almost half the rate of their delayer offspring peers, though with slightly lower deceleration over time.

The inclusion of the maternal background factors in Model 3 showed a radical reduction in the effect of early maternal age on children's mathematics performance at initial status, from a disadvantage of about 11 percentile points to a disadvantage of only about 2 percentile points. Though the coefficient for early maternal age remained statistically significant, a woman's family's socioeconomic status when she was a child, her race, and her own cognitive ability accounted for much of the variance between the scores of children of early starters versus delayers seen in Model 2. For each standard deviation above the mean in family SES that a young woman experienced in childhood, her own child gained, on average, two and a half percentage points in mathematics performance over his peers born to mothers who came from homes represented at the

mean for SES. There was also a positive correlation between a woman's measured cognitive ability and her child's initial mathematics outcomes. Contrastingly, being black or Hispanic put a woman's child at a disadvantage of almost 4.5 percentile points relative to the children of the woman's white peers. There was no effect of maternal background factors on the trajectory or acceleration of scores.

After I added the maternal household factors in Model 4, the effect of an early first birth on initial mathematics score was revealed to be spurious. The statistically significant gap of about 11 percentile points at PPVT-age 5 was reduced to a statistically insignificant gap of about only 1.5 percentile points. While mothers' family's socioeconomic background, their own educational attainment and the income of their families, their cognitive ability and race, and the sex of their child accounted for the association between early maternal age and children's initial mathematics percentile scores, they did not explain the divergence in scores as a result of age, nor did they explain the difference in the acceleration of scores. Only about 7% of the early maternal age effect on age, and none of the early maternal age effect on age² was accounted for by maternal family background and household factors, and only two of these—child's sex and mother's highest grade—were statistically significant. The limited mediational impact of the maternal household factors on the early maternal age-mathematics score trajectory suggests that the hypothesis by Entwisle & Alexander (1992), that children's mathematics skills are rarely improved due to increases to mother's educational attainment because mathematics education is learned primarily in a formal setting, is not far off the mark. Given that mathematics educators are also focused on compensatory learning for those who struggle with the material, it makes sense that scores on

mathematics measures would be largely insensitive to non-school factors, whether moderating maternal background or mediating maternal household factors are considered.

Reading Comprehension Growth

Since the null model including the quadratic term did not provide a good fit, the reading comprehension data estimates were based on a linear equation (see the random effects under Model 1 of Table 2.3). While the effect of an early first birth in Model 2 of Table 2.3 was significantly related to initial reading comprehension percentile scores at PPVT-age 7, it was not related to age ($\beta = -0.191, p = 0.17$). This contrasts with the mathematics data, which revealed, in the absence of controls, that early maternal age was related to initial status, age, and age². The implications are clear. Because children of early child-bearers begin at a disadvantage of almost 11.5 percentile points on the reading comprehension assessment, and because there is no early maternal age effect on age, they remain at a disadvantage throughout the years of formal schooling. The addition of, first, the maternal background and, subsequently, the maternal household controls improves the picture somewhat, but there nevertheless remains a significant impact of early maternal age on children's reading comprehension score at PPVT-age 7. To be sure, about 67% of the early maternal age-reading comprehension outcome was accounted for by the controls, but children of early child-bearers perform, on average, about 4 percentile points lower than their delayer offspring peers.

The statistically insignificant relationship between early maternal age and the linear slope of age in Model 2 changes to statistically significant at the 10% level in Model 4 with the addition of the maternal background and maternal household controls.

The trend, then, is one in which all children tend to decline in their reading comprehension ability, though children born to early child-bearers less so than their peers born to adult child-bearers. Stated more clearly, the gap in reading comprehension scores diminishes over time. An important question is whether this narrowing is due to factors deriving from being born to an early childbearing mother or not, or whether it is perhaps an effect of formal schooling. It is clear that children of early child-bearers start off at a disadvantage with respect to reading comprehension scores. Given the decline over time in reading comprehension ability among all children, it may be the case that the convergent scores of children of early child-bearers with that of their peers born to adult child-bearers is explained by the fact that they have less reading comprehension ability to lose. Alternatively, convergence could be explained by the introduction of children of early child-bearers into formal education where their language skills are improved over and above that of their peers born to adult child-bearers. That is, because they have greater ground they need to make up when they enter school, children of early child-bearers learn and retain more than their peers born to adult child-bearers, which, in turn, allows them to lose less reading comprehension ability over time.

Column 3 of Table 2.4 shows the results of the two-level latent variable regression testing the hypothesis that the convergence in reading comprehension scores is due to differences resulting from being born to an early childbearing mother versus being born to an adult childbearing mother, net of the maternal background and maternal household controls, as well as initial status. Columns 4 and 5 of Table 2.4 show the indirect effect of early maternal age on the reading comprehension trajectory as a function of the differences in outcomes in initial status between children of early child-

bearers and children of adult child-bearers. The results reveal a significant negative association between initial status and reading comprehension growth across categories of maternal age ($\hat{\alpha}_{113} = -0.034, p < .001$), an insignificant direct effect of early maternal age ($\hat{\alpha}_{11} = 0.121, p = 0.299$), and a significant indirect effect of early maternal age ($\hat{\beta}_{11} - \hat{\alpha}_{11} = 0.132, se = 0.030$). This suggests that the association between early maternal age and reading comprehension growth is explained away by differences in the effect of maternal age on reading comprehension scores at PPVT-age 7. Schools, it appears, do not contribute to the convergence in scores between children born to early child-bearers and children born to adult child-bearers. Since there is an overall decline in reading comprehension percentile growth, the narrowing of the reading comprehension gap may be seen as the result of children of early child-bearers having less reading comprehension ability to lose relative to their peers born to adult child-bearers.

Summary of Growth Curve Analyses

With respect to the two outcomes investigated here, the early maternal age-child outcomes relationship, net of the effect of maternal background and maternal household factors, was only shown to be spurious with respect to initial mathematics performance. For mathematics growth, and for initial reading comprehension status and growth, the impact of an early first birth remained statistically significant. Particularly regarding the effect of adolescent first birth on children's initial reading comprehension percentile score, about two thirds of the effect was explained by the addition of the controls. The effects of early maternal age, holding constant the maternal background and household factors, on mathematics and reading comprehension growth also differed. Regarding

mathematics growth and the rate of acceleration, specifically, the addition of controls accounted for little of the impact of an early first birth. The addition of controls to the equation for the linear slope of the reading comprehension data, though, actually led to a decrease in the p value such that the insignificant coefficient in Model 2 became significant at the 10% level in Model 4.

Regarding the hypothesis of a direct effect of early maternal age and related factors on initial mathematics and reading comprehension scores, I put forward the proviso that children's mathematics performance might not be as sensitive to their impact as would children's reading comprehension performance. In confirmation of the literature, that is what I found. As Entwisle & Alexander (1992) have argued, this differential effect of environmental factors on mathematics versus reading ability is probably due to the compensating role that mathematics education plays in the lives of youngsters. Whereas the early home environment is most often characterized by verbal exchanges, with little or no mathematics education, the presence of significant differences in skill attainment related to verbal ability is unsurprising given the unequal distribution among parents of the resources necessary for social capital production in the lives of children. Only after children enter formal schooling might a more direct link between verbal ability and unequal mathematics performance outcomes emerge (Jordan, Huttenlocher, & Levine, 1992).

While the focus of this paper was concerned foremost with the changes to the early maternal age coefficient, I think I should also highlight a clear pattern with respect to both the mathematics and reading comprehension data. First, as is often the case with data investigating academic outcomes, there are significant associations between minority

status and gender and outcomes in initial status and between minority status and gender and outcomes due to age. Blacks and Hispanics fare worse than Whites initially and over time. Males fare worse than females initially, but do better or close the gap over time. Of the other controls chosen, however, those that appear most important to children's initial mathematics and reading comprehension percentile scores range from maternal background factors, such as socioeconomic status and cognitive ability, to maternal household factors, such as family income and education. The families from which mothers come matter just as much to their children's beginning scores as the families those mothers provide for their children. What matters most to score trajectories, on the other hand, is the educational attainment mothers possess.

DISCUSSION

There continues to be an intense debate surrounding the issue of whether there is a significant negative effect of an early first birth on various children's outcomes (Geronimus et al., 1994; Jutte et al., 2010; Turley, 2003). What at least seems apparent is that previously uncontrolled maternal background factors moderate, and maternal household factors mediate, the relationship while nonetheless leaving it significant (Goodman et al., 2004; Pogarsky et al., 2006). Whatever the reported results have been, however, there has been little that has contributed to understanding the early maternal age-child outcomes relationship in a developmental context. Dahinten et al. (2007) provide the only research I know of that makes use of longitudinal data to carry out growth curve analyses testing the early maternal age-child outcomes relationship, a far

superior methodological approach that has previously been applied. Their study, though, focused on adolescents, and most of the outcomes, save one, were behavioral.

The present study makes a unique contribution to the literature in that it utilized a growth model approach to assess the academic trajectories from the very first years of formal schooling through to late adolescence. Like some cross-sectional and family fixed-effect studies, but unlike Dahinten et al. (2007), the present study also controlled for both maternal background and maternal household factors. The results not only suggest a differential impact of maternal age between outcomes, but they also make clear that the predictive power of early maternal age varies between initial status and age. There is no evidence here that early maternal age is not predictive in some capacity. Indeed, early maternal age is detrimental to academic outcomes and its effect is stable throughout the years of formal schooling. No significant association between early maternal age and initial mathematics percentile score was found, but this may reflect the fact that mathematics is primarily learned in a formal school setting. There nevertheless appears to be something unique about being born to an early child-bearer that leads to poorer mathematics outcomes by the end of formal schooling, though some of this may be explained by factors not controlled for here, e.g., school-specific and neighborhood characteristics.

Another unique contribution of the present study is present in the results from the reading comprehension analyses, particularly the latent variable regression analysis. First, regarding Model 3 of the reading comprehension growth curve (Table 3), early maternal age was significantly related to both initial status—with children of early child-bearers faring worse than their peers of adult child-bearers—and age, net of the effects of

maternal background and maternal household factors. The coefficient representing the linear slope of age was negative, indicating that all students' reading comprehension scores fall over time. While children of early child-bearers were more disadvantaged with respect to reading comprehension scores at PPVT-age 7 relative to their peers born to adult child-bearers, however, their declines in reading comprehension as a function of age were somewhat lower, suggesting a convergence in scores over time. Testing whether this convergence was explained by differences present between the two maternal age categories and latent initial status revealed no direct effect of early maternal age, making clear that convergence was an artifact of realities antedating the entrance into formal schooling. I interpreted this as indicating that, because they started with a disadvantage, children of early child-bearers had less reading comprehension ability to lose than their peers born to adult child-bearers.

Limitations

The foregoing analysis has a number of limitations. First, whereas the focus here has been on the relationships of early maternal age and maternal background and household factors to the intercept and age, one might also include age specific information on family income, mother's education, or a host of other aspects of the maternal household. That is, it may be useful for future research to allow maternal household factors to be time-varying rather than time-invariant. For instance, Sullivan et al. (2011), using a cross-section of the Panel Study of Income Dynamics (PSID) data, have shown that mothers whose educations were interrupted due to an adolescent first birth, but who later resumed their studies, provided better home environments for their children than their peers whose educations were also interrupted due to an adolescent first birth but who did not resume

their studies. In my preliminary analysis of these data I arrived at the same results when I compared the time-invariant models to time-varying models, but I also only used two of the more important household factors—family income and maternal education.

Second, it may be the case that different subgroups experience different effects of early maternal age. I noted above, for instance, that, relative to score trajectories, both race and sex matter a great deal, leading to large differences in percentile score achieved. Accepting the proposition, for instance, that Whites and minorities, and boys and girls, occupy different social milieus, there may be different mediating impacts of the early maternal age-child outcomes relationship due to 1) neighborhoods, 2) schools, 3) externalizing behaviors such as fighting or drug use, and 4) peer associations, among other things. To the degree that extreme social disadvantage, coupled with its nonrandom distribution, leads to emotional and mental instability or sickness at a higher rate than would normally be uncovered in the population, the negative feedback makes social disadvantage that much worse. Researchers must somehow also account for the cumulative disadvantage resulting from these realities.

The points in the preceding paragraph also have relevance to the relationship among the moderating background and mediating household characteristics investigated in the present study. There are likely significant interactions among factors not measured here, and between some unmeasured factors and those measured here. Future research might find it useful to stress whether and how the impact of neighborhood or school effects varies across children's level of resiliency or race, or across the range of maternal cognitive ability. Also of interest is the impact that maternal mental health may have relative to children's mental health, both with respect to explaining the early maternal

age-child outcomes relationship and with respect to the relationships between maternal background and maternal household factors and relevant outcomes.

While this study did not explicitly control for the effects of child-specific maternal age—an approach completely in line with the social selection hypothesis of the effects of early maternal age, which highlights no differential outcomes among children born to a mother who began childbearing in the teen years (Moore, Morrison, & Green, 1997)—the social influence hypothesis suggests treating the children born to women in post-adolescence differently than their siblings born when the women were still in the teen years (Jaffee et al., 2001). Whether or not this alternative approach is optimal is unknown, but future research utilizing the methods in this paper could benefit from a comparison of the outcomes. Attendant with this concern would be to use the natural experiment approach of Hotz, McElroy, & Sanders (1997), instrumenting for women who either miscarried or aborted a child while in the teen years and comparing their outcomes. This approach, while it has not revealed differences as large as those between teen and adult mothers, could nonetheless help clarify whether the early maternal age effect is real.

Finally, with respect to the use of the percentile scores rather than the raw scores of children's academic outcomes, it has been argued that they present serious issues to statistical analysis (Brown, 1976; Hopkins, Hopkins, & Glass, 1996; Thorndike, 1997). The assumption, according to Zimmerman and Zumbo (2005), is that populations of test scores are normally distributed. In the case of the NLSY79 and NLSY79-CYA data, however, this assumption is only valid as a consequence of time. The distribution of raw scores of the earliest children of NLSY79 mothers is nonnormal. Therefore, “the distribution of raw scores can be highly irregular” (Zimmerman & Zumbo, 2005, p. 618),

and percentile scores are preferable since in either case its distribution tends to be more rectangular. Given that the percentile scores are also age-normed, this objection was not a major impediment. Small changes in percentile scores from age to age, such as the positive changes seen in the math data and the negative changes seen in the reading comprehension data, are likely to happen since one is always being compared to different reference groups drawn from the population at different times. Indeed, as has been done here, authors of recent published and working papers have used the age-normed percentile scores of academic measures as their dependent variables of interest (Jackson, 2007; Jaeger, 2011).

Conclusion

In conclusion, despite the limitations outlined, the present study makes a unique contribution to the early maternal age-child outcomes relationship literature. With respect specifically to mathematics and reading comprehension initial scores and score trajectories, I have shown the degree to which the effect of an adolescent first birth is accounted for by the combined impact of maternal background and maternal household factors. One of the many concerns first addressed with respect to a showing of an early maternal age effect on children's outcomes was that an ignorance of a young mother's unmeasured background factors was responsible for an overestimation of its impact. Much of the literature has proved this to be true, though in some cases the overestimation has actually been a finding of spuriousness. The present study, having made use of growth curve modeling, which has heretofore been little utilized, underscores the fact that the effect of an early first birth on mathematics and reading comprehension percentile

scores can differ at initial status and as a function of age. Also, in accordance with developmental theory, which states that individuals vary in their rate of development, growth curve modeling provides a better methodological approach to the study of the early maternal age-child outcomes relationship over the range of the life course.

Table 2.1. Family descriptive characteristics by early maternal age status and data source.

Variable	<u>Mathematics Data</u>						<i>t</i> test
	Teen First Birth			Post-teen First Birth			
	<i>N</i>	<i>Mean</i>	<i>SD</i>	<i>N</i>	<i>Mean</i>	<i>SD</i>	
<i>Maternal Family Background</i>							
Mother's Highest Grade Completed	1331	9.60	2.96	2437	11.02	3.16	13.54 ***
Father's Highest Grade Completed	1118	9.44	3.58	2251	11.02	3.97	11.23 ***
Family's Duncan Socioeconomic Index	1099	27.56	18.67	2203	39.89	23.58	15.15 ***
Net Family Income (1979 dollars)	1113	10359.77	8359.55	2057	17551.57	13401.81	16.27 ***
Black or Hispanic	1452	0.58	0.49	2557	0.41	0.49	-10.19 ***
Number of Siblings	1447	4.67	2.92	2556	3.78	2.59	-10.00 ***
Resided in South	1407	0.45	0.50	2468	0.35	0.48	5.97 ***
Delinquency	1284	0.36	8.54	2340	0.06	8.49	-1.01
AFQT Percentile Score	1394	25.08	21.41	2460	43.03	27.73	20.90 ***
<i>Child-Specific & Maternal Household Variables</i>							
Gestation Age	3496	38.66	2.33	4720	38.60	2.13	-1.22
Birth Weight (in ounces)	3586	114.05	21.80	4749	118.07	21.03	8.50 ***
Net Family Income ^a	10958	26628.43	46339.79	16244	57534.18	80220.62	21.30 ***
Mother's Highest Grade ^a	12925	11.15	2.63	18946	13.32	3.05	32.00 ***
PIAT Mathematics Percentile	12989	42.35	25.93	18984	55.92	27.60	44.23 ***
<u>Reading Comprehension Data</u>							
	Teen First Birth			Post-teen First Birth			<i>t</i> test
	<i>N</i>	<i>Mean</i>	<i>SD</i>	<i>N</i>	<i>Mean</i>	<i>SD</i>	
<i>Maternal Family Background</i>							
Mother's Highest Grade Completed	1285	9.58	2.97	2268	11.03	3.16	13.46 ***

Father's Highest Grade Completed	1079	9.44	3.60	2096	11.03	3.98	11.02	***
Family's Duncan Socioeconomic Index	1063	27.59	18.69	2058	39.87	23.63	14.73	***
Net Family Income (1979 dollars)	1071	10471.67	8425.14	1920	17712.24	13354.98	16.05	***
Black or Hispanic	1402	0.59	0.49	2379	0.42	0.49	-10.46	***
Number of Siblings	1398	4.68	2.92	2378	3.75	2.58	-10.22	***
Resided in South	1357	0.45	0.50	2295	0.36	0.48	-5.69	***
Delinquency	1239	0.30	8.54	2180	0.00	8.40	-0.99	
AFQT Percentile Score	1345	25.27	21.59	2292	43.12	27.76	20.25	***
<i>Child-Specific & Maternal Household Variables</i>								
Gestation Age	3270	38.68	2.29	4316	38.61	2.08	-1.31	
Birth Weight (in ounces)	3363	114.05	21.75	4391	118.22	20.91	8.55	***
Net Family Income ^a	8568	27812.56	48911.21	11868	59260.88	78983.28	22.19	***
Mother's Highest Grade ^a	10109	11.19	2.65	13857	13.34	3.18	29.66	***
PIAT Reading Comprehension Percentile	10161	42.71	27.25	13890	55.56	27.05	36.29	***

^aThe *t* test results are based on only the first reported values for the specified variables.

†*p* < .10, **p* < .05, ***p* < .01, ****p* < .001.

Table 2.2. HLM results for mathematics percentile score.

Variables	Model 1	Model 2	Model 3	Model 4
<i>Fixed Effects</i>				
Initial Status at PPVT-age 5, π_{0i}				
Intercept, β_{00}	51.891***	55.285***	51.266***	53.751***
Age at first birth < 20, β_{01}		-11.09***	-2.155 *	-1.529
Maternal Family Background				
Socioeconomic Status, β_{02}			2.544***	2.121 **
Black or Hispanic, β_{03}			-4.363***	-4.589***
Number of Siblings, β_{04}			-0.269	-0.291
Resided in South, β_{05}			-0.359	-0.526
Delinquency, β_{06}			-0.116	0.023
Maternal AFQT, β_{07}			0.247***	0.223***
Child-Specific and Maternal Household Factors				
Male, β_{08}				-4.862***
Gestation Age, β_{09}				0.067
Birth Weight (in ounces), β_{010}				0.022
Family Income (log\$), β_{011}				0.727 *
Mother's Highest Grade, β_{012}				0.531***
Linear Slope (Age), π_{1i}				
Intercept, β_{10}	2.346***	2.753***	2.355***	1.24 **
Age at first birth < 20, β_{11}		-1.283***	-1.057 *	-1.195 **
Maternal Family Background				
Socioeconomic Status, β_{12}			0.255	0.370
Black or Hispanic, β_{13}			0.217	0.386
Number of Siblings, β_{14}			-0.004	0.005
Resided in South, β_{15}			0.307	0.356
Delinquency, β_{16}			0.036	0.032
Maternal AFQT, β_{17}			0.010	0.013
Child-Specific and Maternal Household Factors				
Male, β_{18}				2.036***
Gestation Age, β_{19}				-0.036
Birth Weight (in ounces), β_{110}				0.013
Family Income (log\$), β_{111}				-0.055
Mother's Highest Grade, β_{112}				-0.151***

Quadratic Slope (Age ²), π_{2i}				
Intercept, β_{20}	-0.223***	-0.245***	-0.225***	-0.153 **
Age at first birth < 20, β_{21}		0.089 **	0.092 *	0.104 **
Maternal Family Background				
Socioeconomic Status, β_{22}			-0.016	-0.026
Black or Hispanic, β_{23}			-0.046	-0.060
Number of Siblings, β_{24}			0.003	0.002
Resided in South, β_{25}			-0.031	-0.035
Delinquency, β_{26}			-0.010	-0.009
Maternal AFQT, β_{27}			-0.000	0.001
Child-Specific and Maternal Household Factors				
Male, β_{28}				-0.130***
Gestation Age, β_{29}				0.001
Birth Weight (in ounces), β_{210}				0.001
Family Income (log\$), β_{211}				0.004
Mother's Highest Grade, β_{212}				0.014***
<i>Random Effects</i>				
Initial Status at PPVT-age 5, π_{0i}	598.130***	571.408***	486.577***	475.815***
Linear Slope, π_{1i}	54.466***	54.092***	53.793***	52.039***
Quadratic Slope, π_{2i}	0.311***	0.312***	0.312***	0.304***
% var accounted – Initial Status		4.47%	18.65%	20.45%
% var accounted – Age		0.69%	1.236%	4.46%
% var accounted – Age ²		0.00%	0.00%	2.25%
Reliability – Initial Status	0.42			
Reliability – Age	0.22			
Reliability – Age ²	0.14			
Tau (initial status and age)	-0.54			

Variations rather than standard deviations are entered under the random effects components. Tau refers to the correlation between the initial status at PPVT-age 5 and linear slope.

† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 2.3. HLM results for PIAT reading comprehension percentile score.

Variables	Model 1	Model 2	Model 3	Model 4
<i>Fixed Effects</i>				
Initial Status at PPVT-age 5, π_{0i}				
Intercept, β_{00}	63.875***	67.360***	62.698***	65.808***
Age at first birth < 20, β_{01}		-11.400***	-4.051***	-3.763***
Maternal Family Background				
Socioeconomic Status, β_{02}			2.049***	1.873***
Black or Hispanic, β_{03}			-0.750	-0.388
Number of Siblings, β_{04}			-0.338	-0.337 *
Resided in South, β_{05}			1.489	1.582 *
Delinquency, β_{06}			-0.416	-0.292
Maternal AFQT, β_{07}			0.251***	0.235***
Child-Specific and Maternal Household Factors				
Male, β_{08}				-6.834***
Gestation Age, β_{09}				-0.091
Birth Weight (in ounces), β_{010}				0.062 **
Family Income (log\$), β_{011}				1.034***
Mother's Highest Grade, β_{012}				0.040
Linear Slope (Age), π_{1i}				
Intercept, β_{10}	-2.366***	-2.243***	-2.236***	-2.743***
Age at first birth < 20, β_{11}		-0.191	0.226	0.253 †
Maternal Family Background				
Socioeconomic Status, β_{12}			-0.049	-0.079
Black or Hispanic, β_{13}			-0.687***	-0.764***
Number of Siblings, β_{14}			0.007	0.006
Resided in South, β_{15}			-0.203	-0.241
Delinquency, β_{16}			-0.043	-0.036
Maternal AFQT, β_{17}			0.012***	0.011 **
Child-Specific and Maternal Household Factors				
Male, β_{18}				1.107***
Gestation Age, β_{19}				-0.021
Birth Weight (in ounces), β_{110}				0.003
Family Income (log\$), β_{111}				-0.037
Mother's Highest Grade, β_{112}				0.065***

Random Effects

Initial Status at PPVT-age 5, π_{0i}	468.206***	440.616***	377.544***	363.241***
Linear Slope, π_{1i}	4.538***	4.560***	4.316***	3.921***
% var accounted – Initial Status		5.90%	19.36%	22.42%
% var accounted – Age		0.00%	4.89%	13.60%
Reliability – Initial Status	0.51			
Reliability – Age	0.18			
Tau (initial status and age)	-0.22			

Variances rather than standard deviations are entered under the random effects components. Tau refers to the correlation between the initial status at PPVT-age 5 and linear slope.

† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 2.4. Comparison of HLM and latent variable regressions for PIAT reading comprehension scores.

Predictor	Original	Adjusted	Difference	se of
	Coefficient	Coefficient		
	(Total Effect)	(Direct Effect)	(Indirect Effect)	
Intercept	$\hat{\beta}_{10} = -2.743$	$\hat{\alpha}_{10} = -0.486$	-2.257	0.333
Age at first birth < 20	$\hat{\beta}_{11} = 0.253$	$\hat{\alpha}_{11} = 0.121$	0.132	0.030
<i>Maternal Family Background Variables</i>				
Socioeconomic Status	$\hat{\beta}_{12} = -0.079$	$\hat{\alpha}_{12} = -0.029$	-0.050	0.016
Black or Hispanic	$\hat{\beta}_{13} = -0.764$	$\hat{\alpha}_{13} = -0.773$ ***	0.009	0.029
Number of Siblings	$\hat{\beta}_{14} = 0.006$	$\hat{\alpha}_{14} = -0.006$	0.012	0.005
Resided in South	$\hat{\beta}_{15} = -0.241$	$\hat{\alpha}_{15} = -0.188$ †	-0.053	0.024
Delinquency	$\hat{\beta}_{16} = -0.036$	$\hat{\alpha}_{16} = -0.026$	-0.010	0.010
AFQT	$\hat{\beta}_{17} = 0.010$	$\hat{\alpha}_{17} = 0.019$ ***	-0.009	0.001
<i>Child-Specific & Maternal Household Variables</i>				
Male	$\hat{\beta}_{18} = 1.107$	$\hat{\alpha}_{18} = 0.877$ ***	0.230	0.037
Gestation Age	$\hat{\beta}_{19} = -0.021$	$\hat{\alpha}_{19} = -0.012$	-0.009	0.006
Birth Weight (in ounces)	$\hat{\beta}_{110} = -0.003$	$\hat{\alpha}_{110} = -0.001$	-0.002	0.001
Net Family Income (in log \$)	$\hat{\beta}_{111} = -0.037$	$\hat{\alpha}_{111} = 0.030$	-0.067	0.009
Mother's Highest Grade	$\hat{\beta}_{112} = 0.065$	$\hat{\alpha}_{112} = 0.068$ ***	-0.003	0.003
Initial Status, $\hat{\alpha}_{113}$		-0.034 ***		

† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

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CHAPTER 3

UNDERSTANDING HOW FAMILY SOCIOECONOMIC STATUS MEDIATES THE MATERNAL INTELLIGENCE-CHILD OUTCOMES RELATIONSHIP: A MODERATED MEDIATION ANALYSIS

The covariance between socioeconomic status (SES) and phenotypic IQ is well known in the field of behavioral genetics (Gottfredson, 2011). About 30 percent of the variance in the primary factors that comprise SES indexes is explained by cognitive ability (Neisser et al., 1996, p. 82). Gottfredson (1997), Jensen (1998), and Rowe (1997) have highlighted that tests of intelligence, in both the civilian and military spheres, reveal individuals' ability to appropriate difficult material and they expose the rate at which individuals can learn new material. Taken together, these two factors are strongly predictive of the type of employment individuals can perform well, and, therefore, the amount of income they are likely to earn. Research also shows that higher levels of cognitive ability are required in more prestigious occupations (Gottfredson, 1997, p. 87), and the more prestigious the job the greater the level of remuneration. Moreover, the predictive validity of general cognitive ability for both job performance and training rises with the overall complexity of the work being done (Gottfredson, 1997, p. 82).

Since one of the most studied relationships in social science research is that of parental SES with children's cognitive and academic development (Astone & McLanahan, 1991; Bankston & Caldas, 1998; Smith, Brooks-Gunn, & Klebanov, 1997; Taylor, Dearing, & McCartney, 2004), properly understanding the relationship between

parental SES and phenotypic parental IQ as they act in concert on children's academic performance remains important to the formation of effective policies aimed at closing the class gap in educational outcomes. If in much of the existing social science literature, however, particularly in the field of sociology, the variation in the measures of SES, or social class—e.g., years of education, income, and career prestige—as well as their associations with child outcomes, have been viewed as completely environmental in origin (Rowe, Vesterdal, & Rodgers, 1999), researchers will need to appreciate the fact that part of the variation is genetic. To the degree that parental SES is associated with children's cognitive and academic development (e.g., school grades, psychometric test scores), the relationship is likely genetically moderated given that an underlying heritable characteristic relates to the correlated factors.

For those who have at least recognized the implications that the covariance between SES and phenotypic IQ poses to stratification research, their analyses in the past couple of decades have tended to pit the one against the other rather than investigate the possibility this covariance offers to test interesting hypotheses with respect to their combined effects on children's life chances (Rowe, Vesterdal, & Rodgers, 1999). The origin of this contention dates back to the publication of Herrnstein & Murray's (1994) *The Bell Curve: Intelligence and Class Structure in American Life* and the rejoinders to it. The main argument proffered in that text was that social background was of decreasing importance, and that measured intelligence mattered more, to individuals' likelihood of committing crime, of being unemployed, in poverty, or on welfare, or of providing substandard care for their children, factors that are associated with fewer years of completed education and, hence, the range of career opportunities available. Fischer et

al. (1996), arguing that Herrnstein & Murray's analysis overstated the importance of IQ as a predictor of outcomes, carried out phenotypic regression analyses on the same data used by Herrnstein & Murray, entering a host of additional "environmental" characteristics that the authors did not, and showed the effect of IQ to be nearly equal to, not greater than, that of social context. General criticism of both sets of analyses, though, is that they are incapable of understanding the underlying sources of variation between SES and phenotypic IQ (Jensen, 1998; Rowe, 1994). Whether researchers are studying the relationship of phenotypic parental IQ to child outcomes or parental SES to child outcomes, controlling for parental SES in the case of the former relationship or for phenotypic parental IQ in the case of the latter relationship, leads to the removal of, respectively, shared genetic and shared environmental variance. Except in comparisons of monozygotic and dizygotic twins, or other clever natural experiments, partialling out the true effect of measured parental intelligence on children's life outcomes is perhaps impossible to do well given the broad array of environmental and genetic factors that can be controlled for. Inasmuch as the goal of research with regard to these relationships is to separate the sources of variance, then, phenotypic regression analyses are not the optimal choice of method. Assuming a causal path from phenotypic parental IQ to child outcomes that is perhaps mediated by parental SES, however, it may still be possible to test, using phenotypic regression methods, whether and how said mediation varies across levels of phenotypic parental IQ, a question that has yet to be adequately addressed in the literature.

For instance, research in the field of behavioral genetics—which typically makes use of the twin design and other sibling analyses instead of phenotypic regression

analyses, methods that can actually separate the sources of variance just discussed— contends that children raised in more advantaged homes have more opportunities to engage in the environmental experiences that assist them in reaching their genetic potential for cognitive growth while children from disadvantaged homes do not (Bronfenbrenner & Ceci, 1994; Dickens & Flynn, 2001). McGue (1997) has published research supporting this genotype by environment interaction, finding that family SES positively moderates children’s cognitive ability. Turkheimer et al. (2003) found the heritability of cognitive ability to be greater by a factor of seven in high SES families than in low SES families. More recently, work by Harden, Turkheimer, & Loehlin (2007) and Tucker-Drob et al. (2011) have shown, respectively, the presence of a genotype by environment interaction effect on the cognitive ability among adolescents and infants. This research indicates the influence of high parental SES is likely associated with a stronger correlation between the measured cognitive abilities of parents and their children. Given the positive effect of family SES on children’s cognitive ability, it at least seems apparent that the cognitive ability of disadvantaged children from low cognitive ability homes is likely to rise along with the level of family SES, something social scientists have long argued. What remains unclear is whether the effects of improvements to parental SES on the phenotypic parental IQ-child cognitive ability relationship are the same at all values of the phenotypic parental IQ.

THE PRESENT STUDY

The social environments that parents provide for the children is not independent of parents’ cognitive ability, and, to the degree that environmental variables such as parental

SES predict children's academic performance, part of that effect is explained by the phenotypic expression of heritable genetic traits. The important question is whether the indirect effect of phenotypic parental IQ on child outcomes through parental SES is conditional on phenotypic parental IQ. This paper aims to test a model of moderated mediation, a conceptual model for which is shown in Figure 3.1 (Preacher, Rucker, & Hayes, 2007). Whereas models of simple mediation and simple moderation have been employed in the past to examine the phenotypic parental IQ-child outcomes relationship, this is the first research that integrates the assumptions of both models into one model of moderated mediation. I hypothesized an indirect effect of phenotypic parental IQ on children's academic performance through parental SES that is conditional on the level of phenotypic parental IQ.

[Figure 3.1 About Here]

Given the findings of the genotype by environment interaction in the field of behavioral genetics, in particular, I also posited that the indirect impact of phenotypic parental IQ on children's academic performance via parental SES should be larger at lower levels of phenotypic parental IQ and smaller at higher levels of phenotypic parental IQ. That is, I anticipated larger returns due to gains in parental SES when phenotypic parental IQ was low and smaller returns due to gains in parental SES when phenotypic parental IQ was high.

METHODS

Sample

In order to test the strength of the indirect effect of phenotypic parental IQ on children's academic outcomes via parental SES, I matched mother data from the National Longitudinal Study of Youth, 1979 (NLSY79) with child data from the National Longitudinal Study of Youth, 1979-Children and Young Adults (NLSY79-CYA) for all years from 1986 to 2000. The original NLSY79 sample included 12686 individuals who were between the ages of 14 and 22 as of January 1, 1979, 6283 of whom were females. Of these 6283 women, 451 were in the military and were subsequently dropped from the data in 1984. Because of financial constraints, another 901 women from the economically disadvantaged white oversample were dropped in 1990. With the passage of time, and the attendant growth in NLSY79 women's family size, the weighted mother-child data begins to be representative of a cross-section of women in the United States.

As child assessments were administered biennially, I began with eight rounds of data that could potentially be analyzed. The items contributive to the measure of parental SES, however—which consisted of the standardized values for mother's highest education, her spouses highest education, the maximum value of the Duncan SEI from either the mother or her spouse, and net family income—returned a Cronbach's alpha outside the acceptable range for all years except 1998 and 2000. This constraint of the data limited the analysis here to these two years. Since the present study is focused on only women with children who were assessed on academic instruments, the total sample of females followed up for 1998 and 2000, which was, respectively, 4299 and 4113, actually ranged from a low 836 mothers, representing some 944 children, to a high of

2124 mothers, representing 3386 children, depending on the specific year and outcome. Combining the two years of data revealed, at the low end, 1627 mothers representing 2215 child scores, and, at the high end, 2356 mothers representing 5850 child scores. About half the children in three of the four assessments analyzed here (and outlined below) contributed two scores.

Dependent Measures

Measures of children's performance, returned as a percentile score, are provided for three of the five subtests of the Peabody Individual Achievement Test, Revised (PIAT-R)—i.e., the reading recognition, reading comprehension, and mathematics—and the Peabody Picture and Vocabulary Test-Revised (PPVT-R), and constitute the child outcomes of interest. The complete battery of Peabody assessments, outlined in greater detail below, is both well-normed and standardized and both the PIAT-R and the PPVT-R have high test-retest reliability, are strong in predictive validity, and have been shown to correlate well with other measures of cognitive ability.

Preliminary analysis by year revealed the same results as that given by the combined data, so I use the combined data here. The total number of child scores available for each of the four outcomes, as well as the breakdown by number of scores contributed (whether one or two), are as follows. The reading recognition subtest consisted of 5850 child scores; 2048 children provided one score and 1901 contributed two scores. The reading comprehension subtest consisted of 5009 child scores; 1961 children provided one score while 1524 contributed two scores. There were 5849 child scores on the mathematics subtest of the PIAT-R; 2051 children were assessed once and

1894 children were assessed twice. Finally, the PPVT-R consisted of 2215 child scores, of which only 7 were second scores.

PIAT-R reading recognition. The reading recognition subtest of the PIAT-R, which consists of 84 items of increasing difficulty from preschool to high school level, measures, among children age five and up, how well children recognize words and how well they pronounce the words recognized. Children are assessed on their ability to match letters, name names, and read single words. The completion rate for the PIAT-R reading recognition subtest is a little less than 90 percent, with little difference between racial/ethnic groups. A disparity in completion rates does, however, exist between children of different ages; the oldest and youngest children have below average completion rates compared to children in the middle ages of childhood. Regarding achieved scores, white children have a mean percentile score of 61, with Hispanics following at 52, and blacks still lower at 48. NLSY79 documentation highlights the point that scores on this subtest are increasingly confounded with acculturation factors once children leave the early grades of formal schooling.

PIAT-R reading comprehension. The reading comprehension subtest of the PIAT-R, which consists of 66 items of increasing difficulty, measures children's ability to derive meaning from sentences read silently. Children are assessed on their ability to choose from among four possible picture answers the best portrayal of a sentence's meaning. The PIAT-R reading comprehension subtest is only administered to children who score 15 or higher on the PIAT-R reading recognition test. Completion rates for this measure is lowest relative to the other PIAT-R subtests considered in this study, though, like them, it reveals little evidence of racial/ethnic disparities. The racial/ethnic

disparities on the PIAT-R reading comprehension subtest percentile scores are not dissimilar to those found with respect to the PIAT-R reading recognition subtest. The mean white percentile score is higher than the mean Hispanic percentile score, which is higher than the mean black percentile.

PIAT-R mathematics. Consisting of 84 multiple-choice questions of increasing difficulty, ranging from basic numeral recognition and addition to more complex trigonometry, the mathematics subtest of the PIAT-R measures children's knowledge of concepts and skills taught in mainstream mathematics education. While the test has an overall completion rate of 91 percent, the rate is lower among children above 11 years of age. Completion rates do not vary by race/ethnicity. Racial/ethnic differences do, however, arise with respect to mean percentile outcomes. Again, whites (mean at the 56th percentile) outperform Hispanics (mean at the 42nd percentile), who outperform blacks (mean at the 38th percentile).

PPVT-R. Dunn & Dunn (1981) describe the PPVT-R as measuring “an individual's receptive (hearing) vocabulary for standard American English and provides, at the same time, a quick estimate of verbal or scholastic aptitude.” Consisting of 175 vocabulary items of increasing difficulty, the PPVT-R assesses children's ability to choose from among four picture answers the best portrayal of a word's meaning. Of all the Peabody measures, the PPVT-R reveals the greatest racial/ethnic disparities in mean percentile outcomes. The mean percentile score for whites is nearly twenty points higher than the mean percentile score for Hispanics, and almost 30 points higher than the mean percentile score for blacks. Interestingly, these differences remain strong even after controlling for demographic and socioeconomic controls.

Independent Measure

Maternal AFQT. Assuming assortative mating (Mare & Schwarz, 2006; Watkins & Meredith, 1981), maternal AFQT serves as an indicator of phenotypic parental IQ. The Armed Forces Qualification Test (AFQT), administered to most of the original members of the NLSY79 cohort, is used by the United States Department of Defense to predict maximal performance and to match military recruits to job tasks they can do well (Armor & Sackett, 2004; Hoewing, 2004). As such, it is a very good proxy for the score an individual might receive on a formal test of intelligence, which also has high predictive validity for job trainability, job performance, and the ability to quickly appropriate and manipulate knowledge in dynamic environments (Gottfredson, 1997; Jensen, 1998). Indeed, both the AFQT and formal tests of intelligence are highly correlated with one another, with r averaging about .8 (Herrnstein & Murray, 1994). That nearly 65 percent of the variation in IQ is explained by scores on the AFQT, and vice versa, suggests that both tests are measuring the same underlying trait.

The measured intelligence of parents is expected to correlate well with their children's psychometric test scores, consistent with the behavioral genetics literature that shows cognitive ability to be a largely heritable trait (Jensen, 1998; Rowe, 1994). It should also correlate well with family SES, which has an independent effect on children's academic performance. Since, temporally, intelligence precedes both family SES and children's ability, it is considered in this study as the main independent variable of interest. It is hypothesized to have both a direct impact on child outcomes and an indirect effect on child outcomes via family SES.

Mediator

Family Socioeconomic Status (SES). An SES index was created by standardizing, for each of the two years, 1998 and 2000, the sum of the *z*-transformed values of (1) the natural log of net family income plus 1, (2) the highest grade of the NLSY79 female and her spouse, and (3) the maximum Duncan Socioeconomic Index value, first transformed to deciles, of the NLSY79 female or her spouse. Only women who had at least one child contributing scores on the measures outlined above were included in the calculations. Cronbach's alpha, a gauge of the reliability of multi-item scales, returned a value in the acceptable range of about .75, indicating that a shared underlying trait is being measured by the items in the scale.

Control Measures

The typical demographic covariates of race/ethnicity, sex, and age were also included in each of the four models measuring the conditional indirect effect of maternal AFQT on children's test scores through family SES.

Data Analysis Plan

Missing values of the four independent measures constituting the basis for creation of the family SES index were handled via multivariate imputation by fully conditional specification, or FCS (Raghunathan, Lepkowski, Van Hoewyk, & Solenberger, 2001), using SPSS Statistics 19.0. Also referred to as multiple imputation by chained equations, or MICE, FCS imputes missing values on a variable by variable basis given, or conditional on, information on all the variables observed. The imputations are generated

through a sequence of regression models, differentiated by the type of variable being imputed (e.g., continuous, binary, categorical), in which the covariates include both observed and imputed values for a given individual.

Subsequent to the imputation procedure, indirect (or simple mediation) and conditional indirect effects (or moderated mediation) were assessed in each of the four outcomes. Descriptions of the procedures used follow.

Simple Mediation

While Preacher et al. (2007, p. 211) note that a “significant unconditional indirect effect [or simple mediation] does not constitute a prerequisite for examining conditional indirect effects [or moderated mediation],” I nonetheless carried out preliminary analyses for each of the four outcome measures outlined above by confirming that maternal AFQT has a strong and significant independent effect on children’s psychometric test scores, and then testing whether the direct effect was mediated by family SES (Figure 3.2). To assess the strength of the mediating impact of family SES on the maternal AFQT-child outcomes relationship and to avoid issues arising from non-normally distributed data, I utilized the product-of-coefficients strategy with bootstrapping (Preacher & Hayes, 2004; Preacher et al., 2007).¹ The indirect effect, then, was estimated by first regressing family SES on maternal AFQT (M) and then regressing children’s scores on family SES, controlling for maternal AFQT (Y):

¹ While the product-of-coefficients strategy requires the assumption that the point estimate of the indirect effect be normally distributed, this is usually not the case, even in large samples where the expectation of the point estimate is that it tends toward normality. The standard error used to determine the statistical significance of $\hat{a}_1\hat{b}_1$ is therefore problematic. Bootstrapping overcomes the problems associated with the product-of-coefficients strategy by quantifying the indirect effect as the product of the mean bootstrapped sample estimates of the regression coefficients, where the optimum lower limit of bootstrap resamples is 5000. Confidence intervals are produced using the estimated standard error of the mean indirect effect, and ranges excluding 0 signify that mediation exists.

$$M = a_0 + a_1X + r, \tag{3.1}$$

$$Y = b_0 + c'X + b_1M + r. \tag{3.2}$$

Sample indirect effects were then quantified as products of the mean bootstrapped sample estimates of the regression coefficients \hat{a}_1 and \hat{b}_1 , where \hat{a}_1 refers to the slope coefficient of M regressed on X and \hat{b}_1 refers to the conditional coefficient of Y regressed on M . Given that the unconditional indirect effect is generally given as $c - c'$, where c denotes the effect of X on Y in the absence of M and c' the effect of X on Y in the presence of M , $c - c'$ and $\hat{a}_1\hat{b}_1$ are equivalent.

Moderated Mediation

Preacher et al. (2007) note several cases in which the magnitude of an indirect effect may depend on a moderator. Regarding the graphical representation of simple mediation in Figure 3.2, one can imagine cases in which some fourth variable (W) impacts (1) the a_1 path, (2) the b_1 path, or (3) both the a_1 and b_1 paths. Additionally, a fourth variable (W) may also impact only (4) the a_1 path while a fifth variable (Z) affects the b_1 path. For the purposes of this study, I focused on how the indirect effect of maternal AFQT on children's academic performance via family SES might depend on maternal AFQT. This is a case of the independent variable itself functioning as the moderator of the b_1 path (see Figure 3.1).

As in the preliminary examination of simple mediation addressed above, I tested the hypothesis of moderated mediation in two regression analyses utilizing bootstrapping.

First, I regressed family SES (M) on maternal AFQT (X) (see equation 3.1). I then regressed children's test scores (Y) on maternal AFQT (X), family SES (M), and the interaction between maternal AFQT (X) and family SES (M),

$$Y = b_0 + c'X + (b_1 + b_2X)M + r. \quad (3.3)$$

The dependent variable model represented in equation 3.3 differs from that represented in equation 3.2 in that it now elucidates how the regression of Y on M can be seen as conditional on X . Given a direct effect of maternal AFQT on family SES in the mediator model, a significant interaction effect between maternal AFQT and family SES in the dependent variable model suggested that mediation was indeed moderated.

In cases where a significant interaction was found to exist, I probed the indirect effect by completing regression analyses at the mean and ± 1 SD of maternal AFQT to ascertain the extent to which the indirect effect varied as a function of maternal AFQT. Since the conditional indirect effect is quantified as $f(\hat{\theta}|X) = \hat{a}_1(\hat{b}_1 + \hat{b}_2X)$, the values of X at the mean and ± 1 SD were simply inserted into this equation. I used 95% bias-corrected bootstrapping to achieve more precise confidence intervals on which to judge statistical significance from zero. Preacher et al. (2007) also suggest an extension of the Johnson-Neyman technique to moderated mediation analysis because it allows for easy identification of the value of the moderator for which the indirect effect is just statistically significant ($\alpha = .05$). Additional values of the moderator that are below $\alpha = .05$ constitute the region of significance for the indirect effect, while values greater than $\alpha = .05$ indicate statistical insignificance.

RESULTS

Descriptives

Table 3.1 shows the means, standard deviations and the pairwise correlations for maternal AFQT, family SES, and children's percentile score for each of the four outcomes of interest. Similarities exist across the four data sets with respect to maternal AFQT and the z -standardized value for family SES. Percentile scores, however, fluctuate from measure to measure. Some of this fluctuation could be the result of age at assessment (the PPVT is administered to younger children), but it is likely more attributable to the fact that the mean percentile score of Whites is fairly constant from reading recognition to the reading comprehension to the mathematics portions of the PIAT-R, while the mean percentiles for Hispanics and Blacks differs across these measures. That the mean percentile score of the reading recognition assessment is high relative to the reading comprehension and mathematics assessments is due to the mean percentile scores of Hispanics and Blacks being closer to that of Whites on the reading recognition assessment. Where the mean percentile scores of Hispanics and Blacks are more divergent from the mean percentile score of Whites, as is the case on the reading comprehension and mathematics assessments, the overall mean is depressed.

[Table 3.1 Here]

A cursory look at the pairwise correlations shown in Table 3.1 reveals a consistent relationship among the independent, dependent, and mediator variables for each of the four Peabody measures examined here. Maternal AFQT explains just less than 40% of

the variance in family SES and about 20% of the variance in children's cognitive ability if one excludes the PPVT-R, which indicates that 30% of the variance in child cognitive ability is explained by maternal AFQT. The percentage of variance in child cognitive ability explained by maternal AFQT comports with findings in the literature (Plomin, Defries, McClearn, & McGuffin, 2001). It should be apparent from the correlations shown that, while a huge portion of family SES is explained by maternal AFQT, the relationship between family SES and children's test scores is indicative of a possible mediating effect of family SES on the maternal AFQT-child outcomes association. If maternal AFQT explains 40% of the variance in family SES, and if family SES explains about 15% of the variance in children's ability, it is likely that, in addition to the direct effect of maternal AFQT on child scores, there is an indirect effect of maternal AFQT through family SES.

Simple Indirect Effect

Significant mean indirect effects of maternal AFQT on children's test scores via family SES were found on each of the four Peabody measures. The total indirect effect was $\beta = .1090$ ($SE = .0096$) with a bias corrected and accelerated 95% confidence interval from .0901 to .1280 for the reading recognition subtest of the PIAT-R. The direct effect remained statistically significant ($\beta = .2737, p < .001$), however, suggesting only partial mediation of the maternal AFQT-children's reading recognition score relationship. For the reading comprehension portion of the PIAT-R the indirect effect was $\beta = .0807$ ($SE = .0096$) with a 95% confidence interval from .0616 to .0993, though, again, the direct effect remained strong and significant ($\beta = .3063, p < .001$). The total indirect effect was

$\beta = .0944$ (SE = .0094) with a 95% confidence interval from .0759 to .1129 for the mathematics subtest of the PIAT-R. Maternal AFQT still exerted a significant direct impact of $\beta = .2953$ on children's mathematics performance ($p < .001$) despite partial mediation. Finally, regarding the PPVT-R, the total indirect effect was $\beta = .1165$ (SE = .0153) with a 95% confidence interval from .0852 to .1457. And not unlike the other assessments, the direct effect of maternal AFQT on children's PPVT-R percentile score remained statistically significant when the mediator, family SES, was included in the regression ($\beta = .3817, p < .001$).

Maternal AFQT exerted a stronger influence on each of the respective child outcomes when not controlling for family SES. When family SES was controlled for, however, the total effect of maternal AFQT was reduced by about 30% on the reading recognition subtest, about 20% on the reading comprehension subtest, and about 25% on both the mathematics subtest and the PPVT-R.

Conditional Indirect Effect

I tested the hypothesis of moderated mediation, or conditional indirect effects, on each outcome first by regressing family SES (M) on maternal AFQT (X), the a_1 path denoted in equation 2, and then regressing child percentile scores on maternal AFQT (X), the c' path, family SES (M), the b_1 path, and the interaction between maternal AFQT and family SES, the b_2 path. When they supported the hypothesis of moderated mediation, significant interactions between maternal AFQT and family SES were probed at specific values of the moderator (i.e., maternal AFQT) to ascertain whether and how the indirect effect differed as a function of the moderator.

PIAT-R reading recognition. Results from the regression analysis revealed that family SES was predicted by maternal AFQT; the coefficient represented in the a_1 path indicated that a one percentile increase in maternal AFQT is associated with a $\beta = .022$ ($p < .001$) standard deviation increase in family SES (Figure 3.3). Children's reading recognition scores were predicted by maternal AFQT (c' path; $\beta = .282$, $p < .001$), family SES (b_1 path; $\beta = 8.281$, $p < .001$), and the maternal AFQT by family SES interaction (b_2 path; $\beta = -.072$, $p < .01$), with approximately 20% of the reading recognition ability variance being explained. Stated more clearly, the c' path highlighted that a one percentile point increase in maternal AFQT is associated with an increase of just greater than 1/4 of a percentile point in children's ability on the reading recognition test; the b_1 path showed that a one standard deviation increase in family SES above the mean is associated with an appreciation of 8 percentile points on the reading recognition test; and the b_2 path elucidated that there is a declining mediating impact of family SES on children's reading recognition scores the higher up the maternal AFQT ladder a child's parent is.

[Figures 3.3 – 3.6 About Here]

[Table 3.2 About Here]

In light of the significant relationship between maternal AFQT (the main independent variable) and family SES (the mediator variable), the significant interaction term, b_2 , supported the hypothesis of moderated mediation. I therefore examined whether this conditional indirect effect was significant at specific values of the moderator, which

in this case is also the independent variable. Table 3.2 shows the bootstrapped results testing the hypothesis that the conditional indirect effect equals zero at the mean and ± 1 *SD* of the moderator. The bias-corrected 95% confidence intervals for each outcome measure revealed family SES to have its strongest impact on reading recognition percentile scores for children with mothers at low values of AFQT. Children born to more intelligent mothers, i.e., those one standard deviation above the mean AFQT, also appear to benefit from improvements to family SES, though to a much smaller extent. The indirect effect at one standard deviation above the mean maternal AFQT was less than half the indirect effect at one standard deviation below the mean maternal AFQT.

Utilizing the extension of the Johnson-Neyman technique to moderated mediation, the conditional indirect effect of maternal AFQT on children's PIAT reading recognition score through family SES was shown to be significant between the first ($p < .001$) and just below the 92nd ($p < .05$) percentile of maternal AFQT. Not only did the returns to increased family SES on children's reading recognition scores tend to decrease with increasing values of maternal AFQT, but also they actually disappeared at the very highest levels of maternal AFQT.

Figure 3.7 shows the indirect effect of maternal AFQT on children's reading recognition scores vis-à-vis family SES plotted at all ranges of the moderator with attendant 95% confidence bands. The vertical line indicates the upper boundary of the region of significance, while the horizontal line represents an indirect effect of zero. The lower dashed line representing the lower confidence band approaches zero when the upper limit of the region of significance is reached.

PIAT-R reading comprehension. In agreement with the results yielded from the regression analysis for the reading recognition outcome, the analysis for the reading comprehension scores also revealed that family SES was predicted by maternal AFQT. The coefficient represented in the a_1 path indicated that a one percentile increase in maternal AFQT is associated with a $\beta = .022$ ($p < .001$) standard deviation increase in family SES (Figure 3.4). The c' path suggested that a one percentile point increase in maternal AFQT is associated with an increase of about 1/3 of a percentile point in children's reading comprehension ($\beta = .310$, $p < .001$), about the same effect as was shown in reading recognition analysis. Whereas the reading recognition data showed that a one standard deviation increase in family SES above the mean is associated with an appreciation of 8 percentile points on the reading recognition test, however, the coefficient for the b_1 path for the reading comprehension data was somewhat reduced; the gain to a one standard deviation increase in family SES was greater than 2 percentile points lower ($\beta = 5.889$, $p < .001$). Finally, while the coefficient for the b_2 path was smaller for reading comprehension relative to the reading recognition data, the value nonetheless implied a declining mediating impact of family SES on the maternal AFQT-child outcomes relationship as maternal AFQT increases ($\beta = -.045$, $p < .01$). About 27% of the reading comprehension ability variance was explained.

The significant interaction term, b_2 , again supported the hypothesis of moderated mediation. Probing whether this conditional indirect effect was significant at the mean and ± 1 *SD* of the moderator, family SES was shown to have its strongest impact on children's reading comprehension percentile scores when maternal AFQT percentile scores was low (see Table 3.2). The indirect effect, however, tended to decline such that

the value at one standard deviation above the mean maternal AFQT was half that at one standard deviation below the mean maternal AFQT.

The region of significance of the indirect effect had its lowest bound at the first ($p < .001$) percentile of maternal AFQT and its upper bound at just above the 92nd ($p < .05$) percentile of maternal AFQT. Given that maternal AFQT percentile scores range from 1 to 99, 92 is the largest value of the moderator at which family SES has a mediating impact. Beyond the 92nd percentile of maternal AFQT, the effect on reading comprehensions scores from increases to family SES is negligible. Figure 3.8 shows a graphical representation of the indirect effect plotted at all ranges of the moderator with attendant 95% confidence bands.

[Figures 3.7 – 3.10 About Here]

PIAT-R Mathematics. Figure 3.5 shows that family SES was predicted by maternal AFQT (a_1 path; $\beta = .022, p < .001$). Also, children's mathematics scores were predicted by maternal AFQT (c' path; $\beta = .299, p < .001$), family SES (b_1 path; $\beta = 5.998, p < .001$), and the maternal AFQT by family SES interaction (b_2 path; $\beta = -.037, p < .01$), with 23% of the mathematics ability variance being explained. While maternal AFQT had a positive direct effect on family SES, and while family SES had a positive direct effect on children's mathematics scores, the interaction between maternal AFQT and family SES actually pointed to a weakening of the mediating impact of the latter as values of the former rose.

Given the significant interaction term, I examined how the indirect effect depended on the value of the moderator. Table 3.2 shows the bootstrapped results testing the hypothesis that the conditional indirect effect equals zero at the mean and ± 1 *SD* of the moderator. As was the case with the reading recognition and reading comprehension data, family SES appeared to have its greatest influence on children's mathematics performance at low values of maternal AFQT and decreased as maternal AFQT increased. There was, however, no upper range for the significance of this effect; the extension of the Johnson-Neyman technique to moderated mediation indicated that the indirect effect, while conditional, was significant throughout the range of maternal AFQT (Figure 3.9).

PPVT-R. Figure 3.6 shows, for the PPVT-R data, that family SES was predicted by maternal AFQT (a_1 path; $\beta = .022, p < .001$). Additionally, children's PPVT-R scores were predicted by maternal AFQT (c' path; $\beta = .388, p < .001$), family SES (b_1 path; $\beta = 7.415, p < .001$), and the maternal AFQT by family SES interaction (b_2 path; $\beta = -.045, p < .05$), with 35% of the PPVT-R ability variance being explained. Consistent with the findings of the other three outcomes analyzed here, family SES had a mediating impact on the maternal AFQT-child academic outcomes relationship that was moderated by maternal AFQT. The bootstrapped results testing the significance of the indirect effect at the mean and ± 1 *SD* of the moderator shown in Table 3.2 indicated that the greater the levels of maternal AFQT, the smaller were the returns to children's academic performance with attendant gains in family SES. As in the case of the mathematics data, there was no upper range for the significance of the indirect effect of maternal AFQT on children's PPVT-R scores via family SES. Figure 3.10 shows the conditional indirect

effect to be significant throughout the range of the moderator; that is, the lower dashed line representing the lower confidence band does not approach zero as the region of significance is the entire range of the moderator variable.

DISCUSSION

Focusing on four academic measures, the present study investigated (1) whether there was a mediating effect of the maternal cognitive ability-child outcomes relationship by family SES and, if so, (2) the degree to which that mediation depended on the different levels of maternal cognitive ability. The results buttress findings in the field of behavioral genetics and general social stratification research. Both maternal cognitive ability (here measured on the AFQT) and family SES have a main effect on children's psychometric test score outcomes. Interestingly, however, while family SES mediated some of the effect of maternal AFQT on children's test scores, the effect of family SES on children's scores was conditional on the levels of maternal AFQT. It was apparent in each of the outcomes analyzed that children raised by mothers of low cognitive ability benefitted more from improvements to the social environment than did their peers reared by mothers of higher cognitive ability. Indeed, the pattern that emerged was one in which the positive returns to improvements to the mediating impact of family SES on the maternal AFQT-child academic outcomes relationship declined as the maternal AFQT percentile score increased. Particularly with respect to the two reading assessments, the partial mediation effect of family SES was nonexistent at the very highest levels of maternal AFQT, implying a limited range of the conditional indirect effect.

The findings here are consistent with research published by Bronfenbrenner & Ceci (1994) and Dickens & Flynn (2001), which argued that those raised in disadvantaged environments are at risk for failing to reach their genetic cognitive potential. That is, the combination of having parents of low intelligence and being poor is likely a significantly greater disadvantage for children, developmentally, than being poor only.

The policy implications of the conditional indirect effect explicated in this paper are clear. Money transfers to the cognitively depressed poor could increase the availability of educational resources and opportunities for their children than would otherwise have been had due to their penury. I say “could” if only to stress the fact, as others have done, that income should not be viewed as a “‘multipurpose’ policy instrument” to improve the life chances of children (Mayer, 1997, p. 145; Rowe, 1994). While the literature’s showing of a dampening effect of low SES on children’s cognitive ability and academic development has prompted many scholars to advocate policies such as raising the incomes of poor families as a way to enhance children’s development (Duncan, Yeung, Brooks-Gunn, & Smith, 1998; Garbarino, 1992; McLoyd, 1998), if the reduction of poverty does not at the same time assist parents to accumulate more education, be more involved in their children’s schools and to have relationships with their teachers, and to improve their parenting practices, such transfers will be for naught. This will be especially so for the long-term as opposed to the short-term poor, who are quite different in their social and cultural orientations. Many adults who enter poverty do so for a short time and are often competent caregivers of their children in trying times as they are in more normal circumstances. The long-term poor, in contrast, typically are

less competent and more abusive in the rearing of their children (Seagull & Scheurer, 1986; Taylor et al., 1991). It is generally the case with this group that economic improvements be accompanied by positive social and cultural education to counteract the negative impacts of the non-expectable home environments, dangerous neighborhoods, and poor school curriculums in which their children are immersed. The assumption is clear: the behaviors of the long-term poor are not likely to be improved by increased monetary resources alone, but must be supplemented by changes in attitude and outlook that together round out what is measured in indexes of SES.

Limitations

The present findings have three limitations. The first limitation is minor and has to do with the fact that only one parent's cognitive ability measure was available as the independent variable. Jensen (1998) has stated that the midpoint between both parents' IQ scores is a good starting point for studies attempting to understand the intergenerational transmission of ability. In the absence of full information, however, maternal IQ has been deemed a more important predictor than most social environmental factors. Of course, one cannot ignore the possibility of a low IQ mother representing a high SES household and a high IQ mother representing a low SES household. Admitting the prevalence of assortative mating on both IQ and education (Mare & Schwartz, 2006; Watkins & Meredith, 1981), it is difficult to imagine how any woman could achieve the former condition. There are, however, cases in which it is certainly be possible; many of the blue-collar jobs held by the husbands of low IQ women pay very well and could catapult those families into a higher SES class. Mothers may also reside with family

members who artificially raise their measured SES. It is much less difficult to imagine a case in which a high IQ woman could end up in the lower SES classes; single parenthood is one obvious condition that could cause even higher IQ women to be poor. Whatever the frequency of women residing in a class not commensurate with their level of intelligence, it is considered so small as to not pose a great challenge to the analysis presented in this paper. It is important to remember that the measure of SES is primarily made up of women's and their spouses' education and occupational prestige; any portion of the net family income that is contributed by nonparent sources is assumed negligible. Given these qualifications, the use of maternal AFQT was not considered a major drawback.

The second limitation relates to the general criticism that analyses of child outcomes often ignore child effects. That is, while we typically understand the contexts of children—i.e., the family, the school, and the neighborhood—as shaping, or setting the limits on, what it is they can accomplish (Bronfenbrenner & Morris, 1998), it should be understood that children also influence the environments in which they develop (Knafo & Plomin, 2006; Plomin, DeFries, & Loehlin, 1977; Scarr & McCartney, 1983). Children often actively choose and alter their settings based on both their innate proclivities and learned behaviors and habits. Parents, recognizing the choices that their children make, are influenced to assist in these choices and may therefore augment the extent of their inputs or investments. Within households, parental inputs or investments, then, could differ between children who exhibit disparate propensities for a given trait or behavior. With respect to cognitive and educational inputs, an interesting finding in the literature is that parents in multi-child households allocate familial resources differentially based on

the dissimilarities in ability observed among their children (Ayalew, 2005; Frijters, Johnston, Shah, & Shields, 2010; Rosenzweig & Schultz, 1982). Scholars wishing to replicate the findings of this study, focusing perhaps on parenting behavior rather than family SES, may find it useful to in some way account for child effects as another potential moderator of the mediating pathways. For the purposes of the present study, child effects may certainly play a role, but given the focus on family social status rather than parenting behavior, the ignoring of child effects was also not viewed as a major drawback.

The third limitation derives from what Sir Francis Galton called the *reversion to the mean* or the *law of filial regression to mediocrity*. Regarding all heritable traits, the parent-offspring genetic correlation of .50 (because a child receives one-half of his genes from each parent) is complemented by either a corresponding parent-offspring phenotypic correlation that is larger than the parent-offspring genetic correlation or a corresponding phenotypic correlation that is smaller than the parent-offspring genetic correlation (Jensen, 1998). In the case where a trait is more influenced by nongenetic than genetic factors, the greater will offspring tend to deviate from the same trait exhibited phenotypically in their parents. To take height as an example, an unusually short man's sons may receive a level of nutrition that leads to a large drop in the parent-offspring genetic correlation of .50, causing the sons to be taller than their father. The more a trait is dependent on both genetic and nongenetic factors, as intelligence is, the greater the likelihood of a regression toward the mean. To the extent that such a phenomenon is widespread within generations, it could be problematic for interpreting results. What if the effect one is seeing is simply a result of a regression toward the

mean? The child of a poor, low IQ mother who has regressed *up* toward the mean could do unusually well regardless of the mother's SES and ability. Alternatively, the child of a well-to-do, high IQ mother who has regressed *down* toward the mean may fare poorly academically despite the superior resources of the home.

Conclusion

In conclusion, both phenotypic measures such as cognitive ability and environmental measures such as SES play an important role in predicting individuals' life outcomes. Neither should be ignored in interpretations of the effect of the other, but both should be seen as working best in concert. To the extent that improvements to family social status can lead to an expectable environment (Curtis & Nelson, 2003; Bruer & Greenough, 2001)—i.e., an environment conducive to uninhibited learning such that children achieve at a level that otherwise would have been unattainable—for children raised in low cognitive ability households, both family social status and parental ability must be seen as consequential for the long-term outcomes of children.

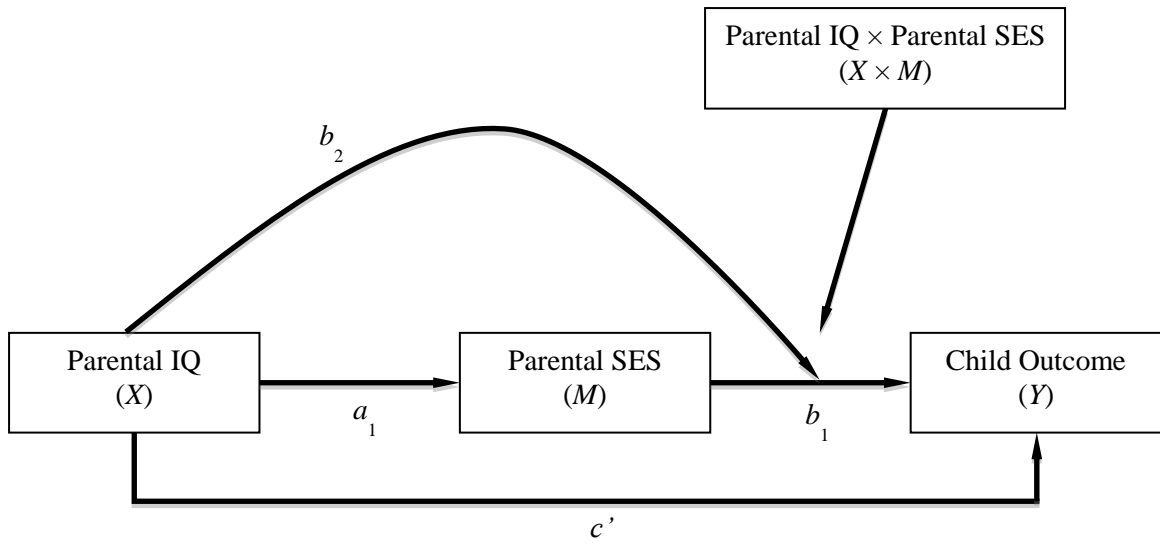


Figure 3.1. Conceptual moderated mediation model in which the independent variable moderates the mediated path.

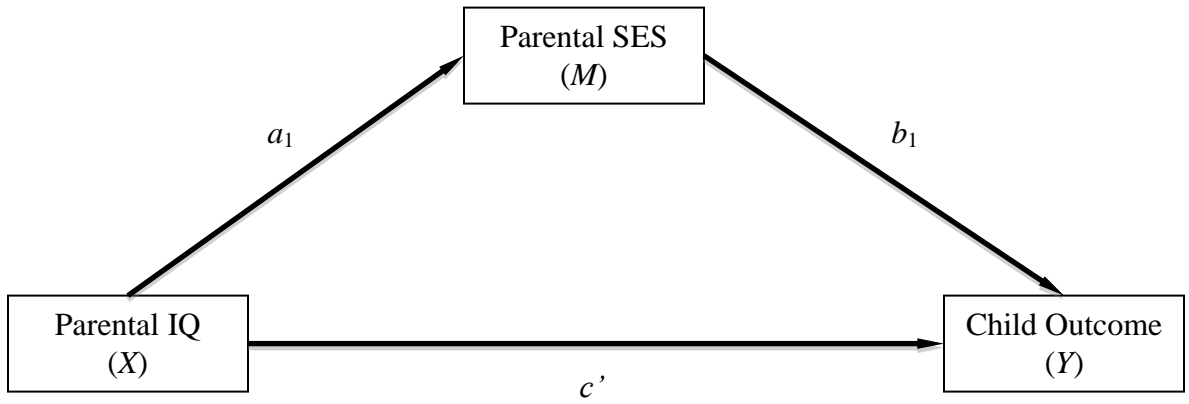


Figure 3.2. A model of simple mediation.

Table 3.1. Means, standard deviations, and pairwise correlations for maternal AFQT percentile score, family SES, and children's percentile scores (all measures).

	PIAT Reading Recognition <i>n</i> = 5850			PIAT Reading Comprehension <i>n</i> = 5009		
	(1)	(2)	(3)	(1)	(2)	(3)
Mean	38.98	-0.74	59.35	38.44	-0.78	51.82
Standard Deviation	28.40	0.97	28.80	28.20	0.95	28.10
Maternal AFQT (1)	-			-		
Family SES (2)	.61***	-		.60***	-	
Child Percentile Score (3)	.41***	.36***	-	.45***	.37***	-

	PIAT Math <i>n</i> = 5849			PPVT <i>n</i> = 2215		
	(1)	(2)	(3)	(1)	(2)	(3)
Mean	39.01	-0.74	53.69	39.78	-0.68	41.32
Standard Deviation	28.41	0.97	27.96	28.55	1.00	31.26
Maternal AFQT (1)	-			-		
Family SES (2)	.61***	-		.59***	-	
Child Percentile Score (3)	.45***	.37***	-	.55***	.42***	-

Note: *** $p < .001$.

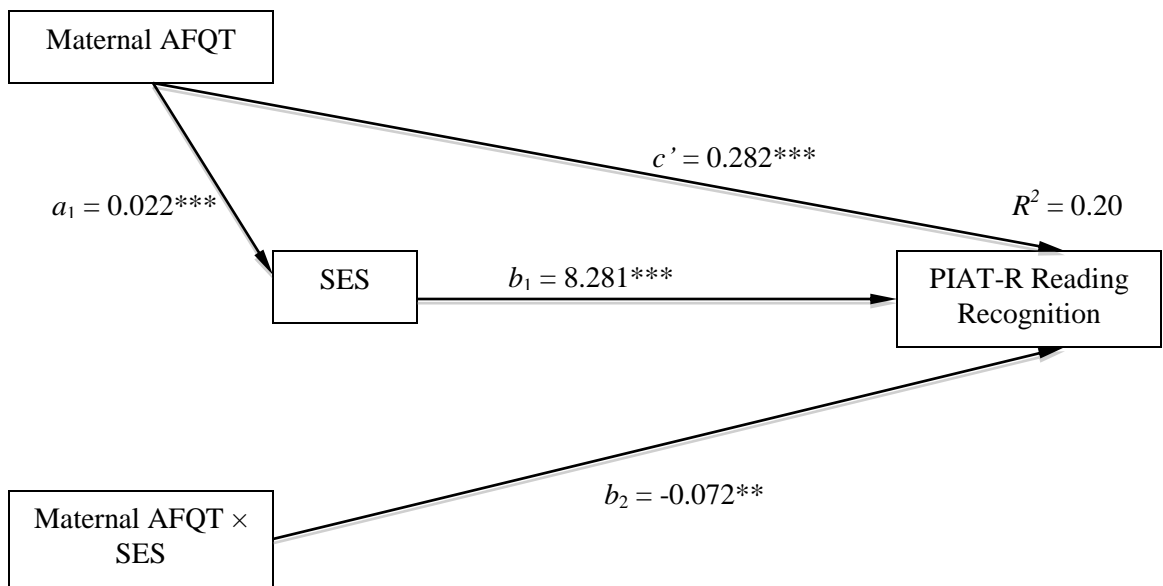


Figure 3.3. Results of regression analysis for moderated mediation of PIAT-R reading recognition outcome.

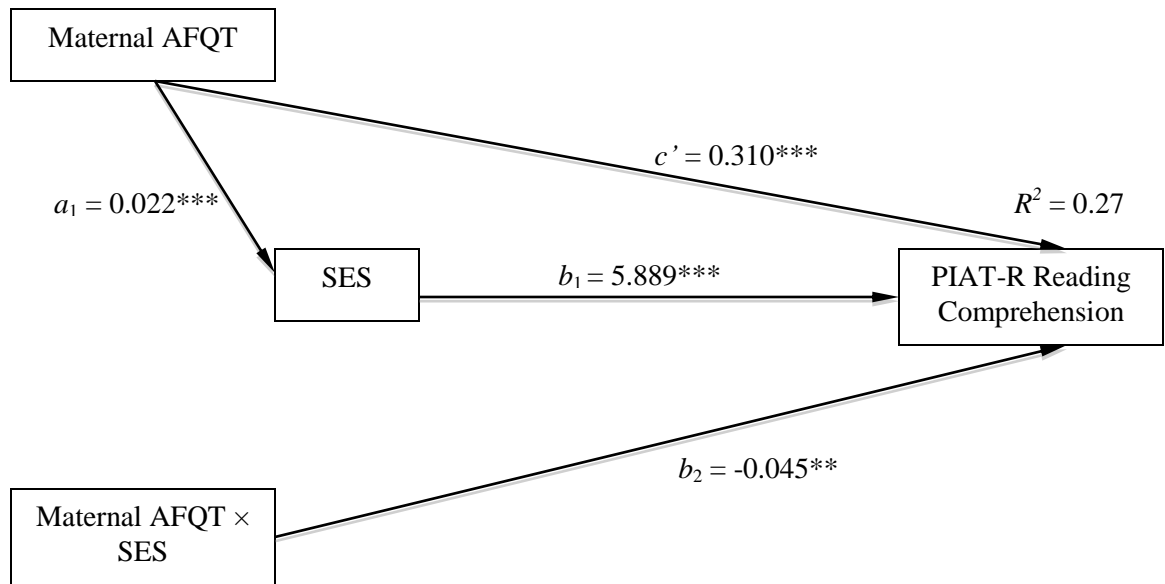


Figure 3.4. Results of regression analysis for moderated mediation of PIAT-R reading comprehension outcome.

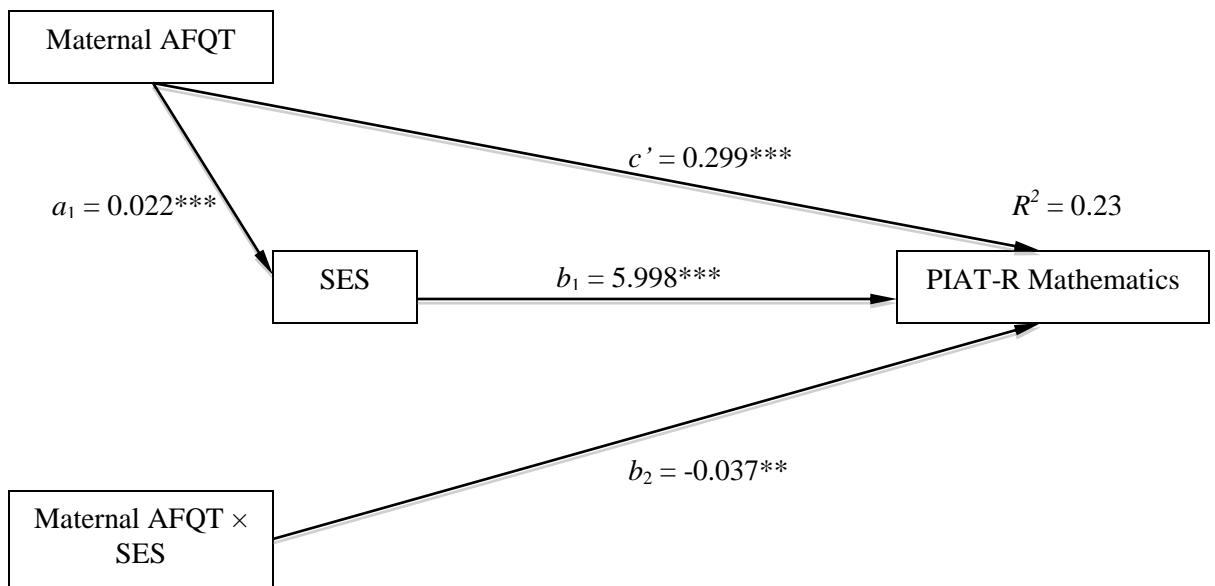


Figure 3.5. Results of regression analysis for moderated mediation of PIAT-R mathematics.

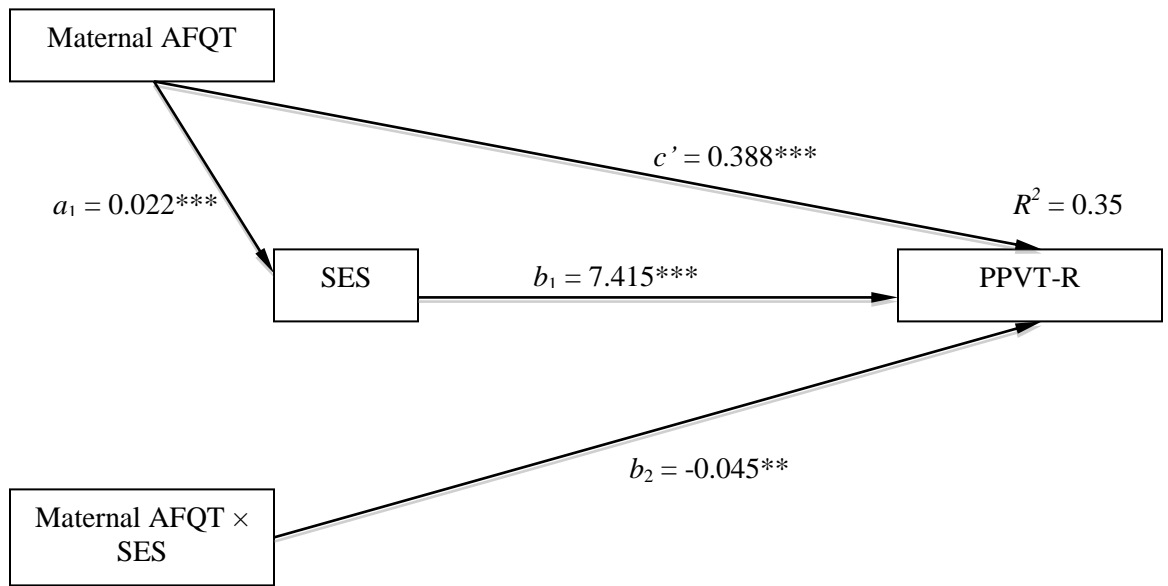


Figure 3.6. Results of regression analysis for moderated mediation of PPVT-R outcome.

Table 3.2. Bootstrapped indirect effects of maternal AFQT on children's percentile scores at the mean and ± 1 SD (all measures).

Maternal AFQT	PIAT-R Reading Recognition				PIAT-R Reading Comprehension			
	β	s.e	LL BC ^a	UL BC ^b	β	s.e	LL BC	UL BC
-1 SD	0.165***	0.014	0.138	0.192	0.116***	0.014	0.089	0.143
Mean	0.120***	0.010	0.101	0.141	0.088***	0.010	0.068	0.107
+1 SD	0.076***	0.011	0.056	0.096	0.059***	0.011	0.038	0.080
	PIAT-R Mathematics				PPVT-R			
	β	s.e	LL BC ^a	UL BC ^b	β	s.e	LL BC	UL BC
-1 SD	0.123***	0.013	0.097	0.150	0.152***	0.021	0.113	0.191
Mean	0.100***	0.009	0.082	0.119	0.124***	0.015	0.094	0.155
+1 SD	0.077***	0.011	0.058	0.097	0.095***	0.017	0.060	0.130

Note: *** $p < .001$, ** $p < .01$, * $p < .05$; $N = 5000$ bootstrapped samples. ^aLL BC refers to the lower level of the bias corrected 95% confidence interval. ^bUL BC refers to the upper level of the bias corrected 95% confidence interval.

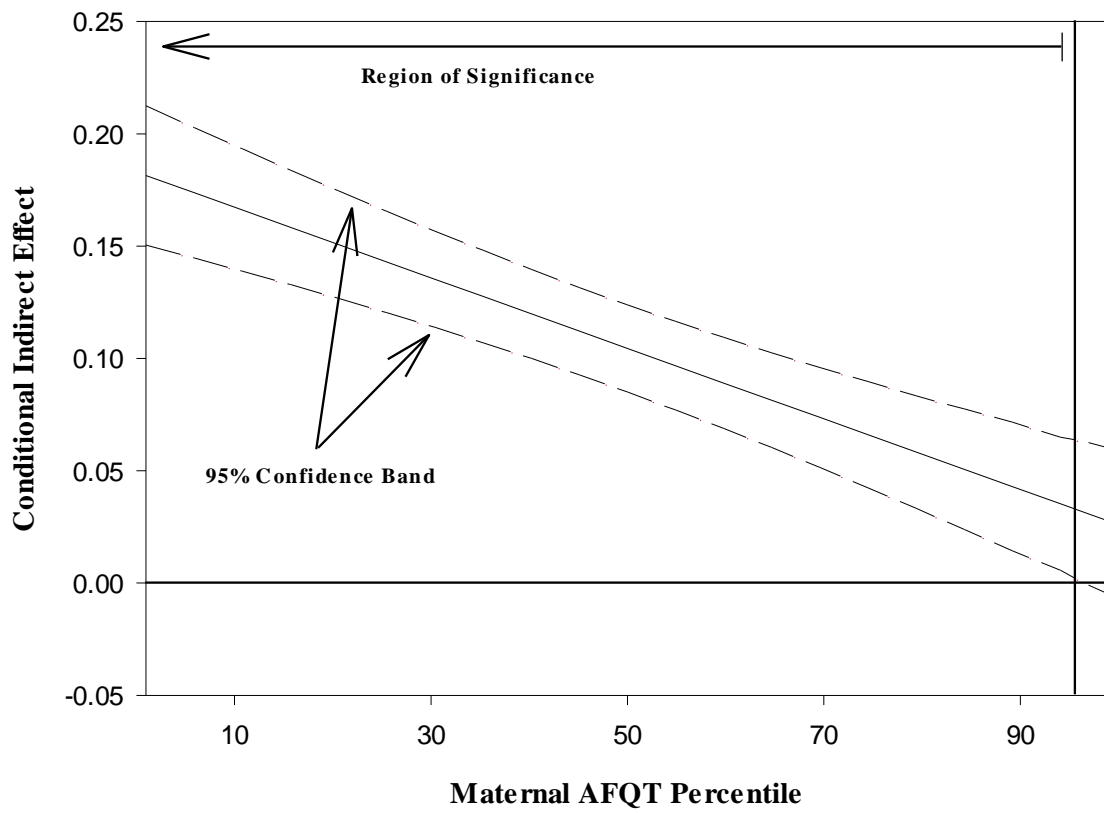


Figure 3.7. Moderated indirect effect of maternal AFQT percentile scores on children's PIAT-R reading recognition percentile scores through family SES with 95% confidence bands.

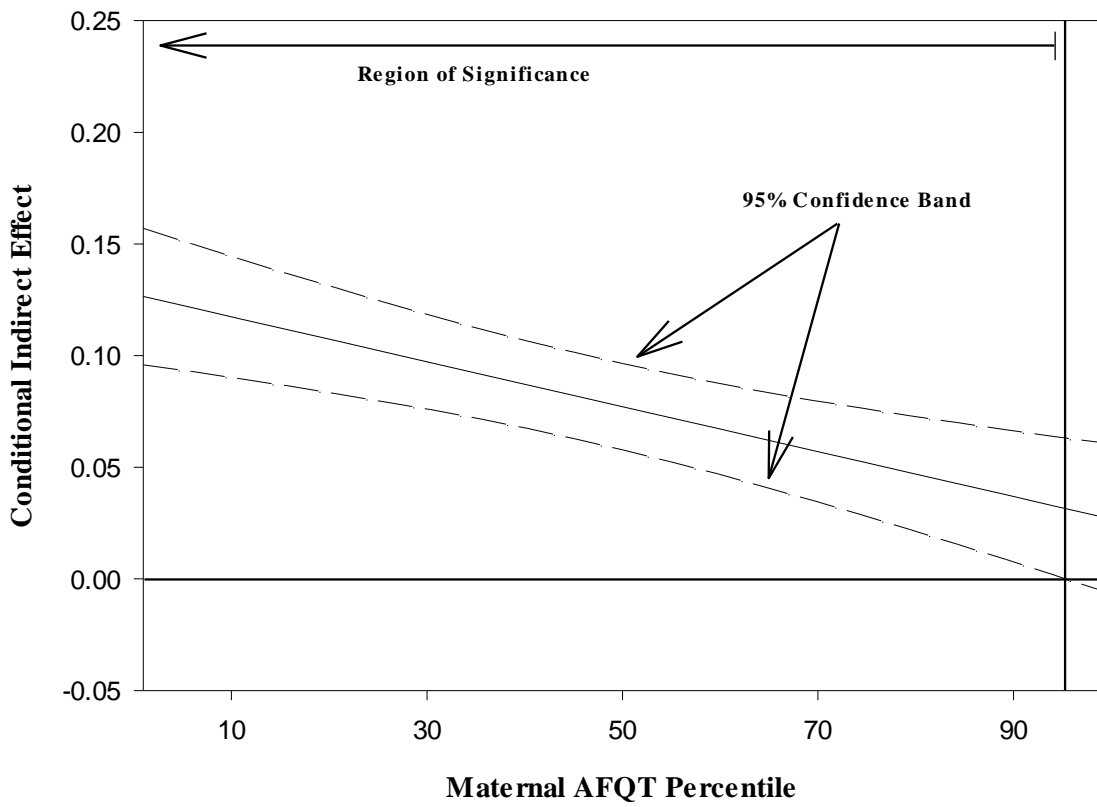


Figure 3.8. Moderated indirect effect of maternal AFQT percentile scores on children's PIAT-R reading comprehension percentile scores through family SES with 95% confidence bands.

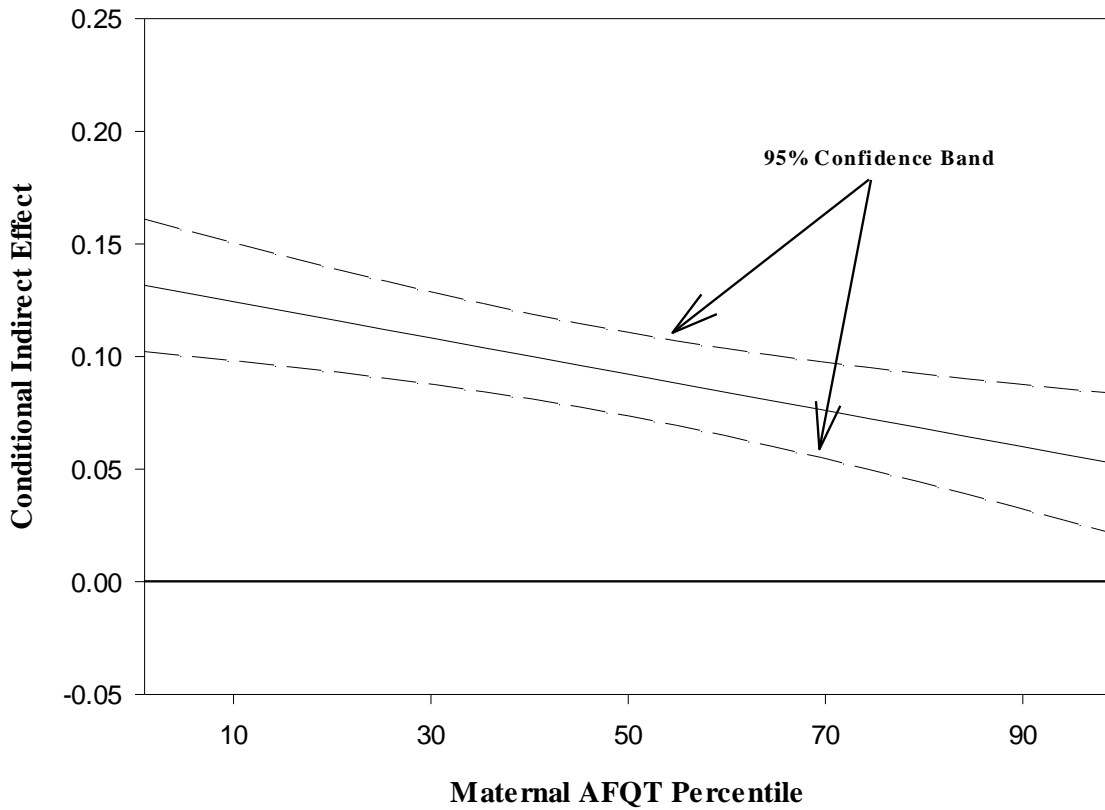


Figure 3.9. Moderated indirect effect of maternal AFQT percentile scores on children's PIAT-R mathematics percentile scores through family SES with 95% confidence bands.

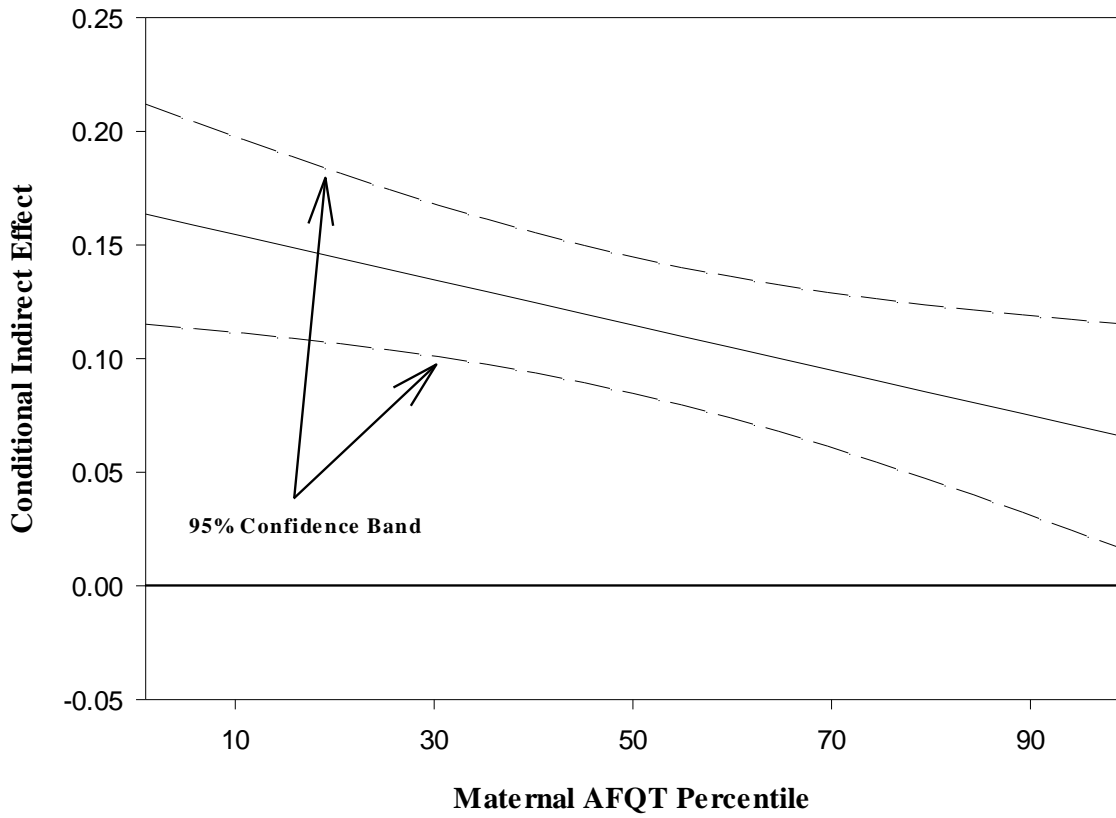


Figure 3.10. Moderated indirect effect of maternal AFQT percentile scores on children's PPVT-R percentile scores through family SES with 95% confidence bands.

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CHAPTER 4
**THE EFFECT OF PRESCHOOL INTERVENTIONS DEPENDS
ON MATERNAL IQ: A REEVALUATION OF THE
CAROLINA ABECEDARIAN PROJECT DATA**

In the past forty years a number of small-scale early educational interventions have been created and tasked with the objective of attempting, or testing whether it is possible, to prevent developmental delays via environmental improvements in the lives of at-risk children (Garber, 1988; Gray, Ramey, & Klaus, 1982; Ramey et al., 1988; Schweinhart, Barnes, & Weikart, 1993). Whether the assessment of risk for inclusion in these studies centered on the well-known biological causes of depressed cognitive functioning, such as malnutrition or low birth weight, or whether it highlighted social environmental causes rooted in family poverty (e.g., limited access to educational resources or use of harsh parenting practices), itself correlated with many biological causes, it was supposed that raising the quality of the social environment for preschool age children could avert, specifically, the incidence of mild mental retardation (i.e., $50 \leq \text{Full-Scale IQ (FSIQ)} \leq 70$).¹ The goal was praiseworthy given the unusual prevalence of stunted cognitive ability among those in the lower socioeconomic stratum (Susser, Watson, & Hopper, 1985). That the distribution of more severe forms of mental retardation is spread more evenly across different social classes, and mild mental retardation is not, suggests a dampening effect of poverty on the attainment of some individuals' intellectual potential

¹ All instances of intelligence quotient (IQ) that appear in this paper refer to full-scale IQ.

such that they often test lower on IQ tests than they might have had they been reared in better circumstances.

Interestingly, the intervention literature has tended to present the link between socioeconomic status and depressed cognitive ability as primarily an intergenerational social phenomenon. Parents' social class or socioeconomic status (SES), it is argued, particularly the goods it may purchase, from more positive parent-child interactions to toys to books and other resources conducive to an "expectable" child environment (Bruer & Greenough, 2001; Curtis & Nelson, 2003), is the proximal predictor of child cognitive outcomes. Considerations of nonsocial factors that might perhaps mitigate or moderate environmental intervention effects have, particularly in post-treatment analyses, been too few. There are two ineluctable and related facts, in particular, that complicate the clean causal chain from parents' SES to child cognitive ability that should be of analytic interest to intervention researchers. First, it is well established that mental abilities are largely heritable (Brody, 1992; Mackintosh, 1998; Plomin, 1999; Snyderman & Rothman, 1988). Whether or not this fact precludes the possibility of raising—or, as is often the case in intervention studies, preventing delays in—cognitive ability is a question of vital importance. Second, socioeconomic status and its attendant correlates are not dependent only on those personal individual characteristics under environmental influence, but are likewise impacted by genetic factors, including those factors contributive to intelligence (Bouchard & McGue, 2003). The association between parental SES and child IQ is strong because both are correlated with the common predictor parental mental ability.

To elaborate on the first point, it is important to stress at the outset the fact that, while the phenotypic expression of a genotype will always depend to some degree on exposure to a typical environment (e.g., the heritability of height likely depends on some combination of proper diet and regular, unrestrained physical movement), the reality that IQ is heritable implies that its measure is not, as Sternberg & Wagner (1993) have argued, merely a measure of narrow academic aptitudes that are real only insofar as industrialized society privileges them. IQ, rather, is suggestive of a latent genetic trait that is not only determinative of one's ability to adeptly handle tasks of increasing difficulty and complexity, to see relationships, and to problem solve (Carroll, 1993; Gottfredson, 2011; Jensen, 1998), but is also embodied in human physiology and transmittable to offspring. While IQ certainly reflects environmental as well as genetic inputs, then, it is generally accepted that its broad heritability (i.e., the combination of all genetic factors impacting the development of the phenotypic trait) is about .70, or 70%, in the general population, with the smallest proportion of its variance, 30%, attributable to nongenetic causes (i.e., shared and nonshared environment). From this one should infer that, regarding the assessment of risk utilized by the various intervention studies, parental IQ figures prominently for child cognitive outcomes, perhaps more so than does a suboptimal environment.

Of course, the long-held assumption that all intellectual retardation not deriving from organic disease or pathology is the result of social and cultural deprivation is one that was long ago been belied by findings from the Milwaukee Project (Garber, 1988), a longitudinal investigation of the risk factors for deceleration in the rate of intellectual development. The once principal investigator of the Milwaukee Project, Rick Heber,

while preparing the fifth edition of the *Manual on Terminology and Classification in Mental Retardation* (1959), and prior to initiation of the Milwaukee Project, began to question what was becoming interpreted as the causal relation between the environmental realities often associated with poverty and intellectual retardation. What Heber discovered was that the cultural deprivation often associated with the intellectual delays of children and believed to derive from their parents' strained economic conditions, was more the result of the stunted intellectual development of parents rather than poverty per se. While there was certainly a higher rate of child intellectual retardation in the subpopulation of the economically disadvantaged, it was mostly the intellectually limited parents, the majority of whom occupy this stratum, who often produced cognitively delayed children. The children of economically disadvantaged higher IQ parents exhibited a more normal cognitive developmental progression. Poverty, then, did not seem to have a universally inhibiting effect on development.

Testing the hypothesis that the risk factors for deceleration in the rate of intellectual development were due to parental IQ—what they referred to as familial factors—rather than social or cultural deprivation, Heber and his colleagues' prospective work highlighted the need for preventive researchers in the area of intellectual functioning to concentrate risk within the larger universe of children from low socioeconomic backgrounds so as to eliminate excessive false positives and to ensure that the majority of those selected for inclusion in a study ultimately demonstrated delays in their rate of intellectual development (Heber & Dever, 1970; Heber, Dever, & Conry, 1968). Their conclusion, based on findings from cross-sectional surveys, was that a maternal IQ level of 75 or lower is a much more reliable predictor for deceleration in the

rate of intellectual development than is a broad indicator like socioeconomic status or other demographic variables.

Research continues to confirm that maternal IQ, more so than any of the traditional environmental causes investigated in the social sciences, is the most significant predictor of child cognitive outcomes. Confirming the earlier findings of Heber and his colleagues, Feldman and Walton-Allen (1997), for instance, showed that poor mothers with mental retardation (i.e., IQ below 70 in their analysis) were more likely to have children with low IQ than poor mothers without mental retardation. More generally, Bacharach and Baumeister (1998), in their study of low birth weight babies, found maternal IQ accounted for 53% of child IQ variance, which was magnitudes greater than the 10% of child IQ variance explained by family income or the negligible amount explained by the home environment. Keltner, Wise, and Taylor (1999) have shown that normal weighted, full-term babies born to low IQ mothers have a greater likelihood of achieving lower scores on the mental development (MDI) and psychomotor development indexes (PDI) of the Bayley Scales of Infant Development (Bayley, 1969), in addition to a greater likelihood of performing poorly on cognitive and academic measures administered into adolescence and adulthood, compared to those born to mothers with IQs above 84. As the children of low IQ mothers age, they also have a greater odds, compared to the children of normal IQ mothers, of being retained in grade and of needing special education. Another study of Chilean high school graduates found that maternal IQ had a stronger association with child IQ scores than did socioeconomic status (Ivanovic et al., 2002).

The second point, that socioeconomic status is an effect of genetic factors, invokes Herrnstein's syllogism, which was first articulated about 40 years ago in the *Atlantic Monthly* (Herrnstein, 1971). If, in the general population, mental ability, or IQ, is heritable, and if individuals' position within the socioeconomic hierarchy depends on that ability, then socioeconomic status is itself heritable. It is entirely intuitive that, since many environmental factors tend to covary with genetic factors, one should infer that environments are to some extent inherited. For instance, IQ, the variation of which is explained largely by genetics or some general factor, is high in practical validity, predicting outcomes relative to educational achievement and job performance, which are themselves temporally succeeded by (i.e., predictive of) earnings and other aspects of socioeconomic status (Carroll, 1997; Gottfredson, 1997; Jensen, 1998; Neisser et al., 1996).

Table 4.1, adapted from Gottfredson's (2011) treatment of research originally completed by Jencks et al. (1979), makes the point more clearly. Shown are average intra- and intergenerational correlations between fathers' and sons' personal characteristics and economic success. Granting IQ heritability estimate of .70, the logic of Herrnstein's syllogism becomes rather apparent when assessing the path from son's IQ to son's educational attainment, occupation, and earnings ($r = .57$, $r = .46$, and $r = .28$, respectively), from son's educational attainment to son's occupation and earnings ($r = .61$ and $r = .38$, respectively), and from son's occupation to son's earnings ($r = .43$). The 37% of son's occupation variance that is explained by son's education is partially accounted for by son's IQ, which explains about a third of the variance in son's education. The same may be said for the intragenerational relationship between

education and earnings and between occupation and earnings. For each of several factors that usually compose the index of socioeconomic status, some of the variance in outcomes is explained by genetic inputs. Assuming these sons had sons, and the correlations between son's and sons of son's various characteristics were not different from those between fathers and sons shown in Table 4.1, the picture is one in which the heritability of education, occupation, and earnings overlaps with the heritability of IQ. Such an inference is consistent with the findings in the literature (Rowe, Vesterdal, & Rodgers, 1999). Individuals seem, then, to settle into the socioeconomic stratum—and the attendant habits, attitudes, behaviors, and frame of mind—that is commensurate with their degree of intellectual sophistication, or IQ, a largely heritable trait.

[Table 4.1 About Here]

Individuals of low intelligence, in particular, often exhibit antisocial behavior, usually beginning in childhood, which is an increased risk factor for chronic unemployment (an obvious cause of poverty), violence, criminality, and other issues related to poor socialization in adulthood (Hinshaw, 1992; Koenin et al., 2006; Moffitt et al., 2002; Moffitt & Lynam, 1994; Nigg & Huang-Pollock, 2003; Simonoff et al., 2004). Thought to be related to a deficit in verbal acuity, the impact of the tendency toward behaviors detrimental to positive life outcomes among persons of low intelligence is both robust and independent of race, class, and differential detection of delinquency (Lynam, Moffitt, & Stouthamer-Loeber, 1993).

While the heritability of mental abilities and, by extension, social class and the correlates related to childrearing, *prima facie* appear to belie the major assumptions of intervention studies, the interactive effects between them in post-treatment analyses may nonetheless help qualify findings of no long-term significant gains in development deriving from such programs. For instance, with respect to the issue of heritability, specifically, it is well known that it tends to be lower, i.e., around 40%, in early childhood (Jensen, 1998; Pedersen, Plomin, Nesselroade, & McClearn, 1992; Plomin et al., 1994), which means there remains a good deal of variability left to be explained by shared environmental effects. That the quality of the environment, however, matters more for those in poverty than for those not in poverty (Farkas & Beron, 2004; Luster & Dubow, 1992; Turkheimer, 1991) indicates, in accordance with the hypothesis put forth by Scarr (1992) and confirmed by Turkheimer et al. (2003), that IQ heritability should be uncommonly low and the effects of the shared environment uncommonly high among those reared in the worst environments. That bright children from low SES backgrounds differ markedly in their educational attainment than their bright peers from higher SES backgrounds underscores this point (Gottfredson 1981). If the ratio of shared environmental variation to phenotypic variation is large in early childhood, then policies designed to reduce the disparity in material advantage between the poor and the privileged must go a long way in helping the former achieve a level of ability that might otherwise have been unattainable (Jencks, 1980; Rowe, 1994). Interventions, which typically are quite intensive, provide one of the better opportunities to close the environmental gap. Recent research regarding regular center-based care reveals it is often of higher quality than the care provided in-home by families (Li Grining & Coley,

2006). General day care is also linked to school readiness, which is foundational to later achievement (Magnuson, Ruhm, & Waldfogel, 2007).

In the current study, I examined whether resource improvements in the lives of a homogeneous sample of at-risk youngsters participating in a longitudinal randomized trial led to appreciable gains in their IQ scores, focusing on both the extent to which gains were explained by maternal IQ and whether positive impacts of treatment were dependent on maternal IQ. I also compared the growth in scores among children of mildly mentally retarded, borderline, and average IQ mothers. Given that the children of poor, low IQ mothers are at greatest risk of failing to reach their genetic potential, I sought to explicate whether treatment group gains, relative to control group gains, were larger for these children than were the corresponding gains experienced by children of higher IQ mothers. Finally, since gains from interventions tend to disappear over time, I also investigated the additional question of whether the deceleration in gains varied by maternal IQ.

METHOD

Sample

I utilize data from the 15-year old follow-up of the Carolina Abecedarian Project. The original sample of 111 children—born between 1972 and 1977 and considered to be at high-risk for developmental delays and school failure based on an experimental 13-item index—was divided into two groups at study inception: 54 were assigned to the preschool control group and 57 were assigned to the preschool experimental group. Experiment was center-based and included an intense curriculum called Learningames

(Sparling & Lewis, 1979, 1984), which contributed to the creation of a stimulating environment that served to enhance the cognitive and emotional development, as well as language competence, of the included children. Infant games and activities were tailored to the needs of each child by center staff to maximize the anticipated positive effects of the intervention. Open eight hours a day, five days a week, twelve months a year, for five years, center-based services also included the provision of nutritional meals for children during the school day and transportation for the children of parents who, for whatever reason, could not get them there. Teacher education, which ranged from high school to master's level, was buttressed with required semi-annual in-service training, which contributed both to the low turnover rate during the program's duration and to constancy in the children's lives. Also, teacher to child ratios were 1:3 for infants and toddlers, 1:4 for 2-year olds, and 1:6 for 3-5 year-olds. The demographic characteristics of subject participants at the inception of the study reveal that 98% were black and 75% came from a single-parent or multigenerational household. The mean maternal age was about 20-years old, the mean maternal education acquired was about 10 years, and the mean maternal IQ was just below 85. These numbers were basically the same when broken down by treatment versus control group assignment. To control for the effects of differential nutrition intakes, control children received the same supplemental meals that treatment children received.

Dependent Measure

Child IQ Test Scores. To test the effectiveness of the preschool intervention, highly reliable and valid standardized psychometric IQ tests were individually administered to

children in both the control and experimental groups at several points during and after the trial period. For the purposes of the present analysis, I chose as the outcome of interest the Stanford-Binet (Terman, 1973), administered at ages 2, 3, and 4, the Wechsler Preschool and Primary Scales of Intelligence (WPPSI; Wechsler, 1967), administered prior to program termination at age 5, and the Wechsler Intelligence Scale for Children-Revised (WISC-R; Wechsler, 1974), administered at ages 6 ½, 8, 12, and 15. Typically utilized as a tool for school placement, or to determine the presence of developmental delay or a learning disability, scores on both the Stanford-Binet and the Wechsler scales have been found to approximate a normal distribution, with mean at 100 and standard deviation at about 15. Scores on the former are highly correlated with scores on the latter, and both predict very well socioeconomic status later in life, with lower scores generally leading to mundane and repetitive work with low prestige and low pay and higher scores generally leading to intellectually demanding work with higher prestige and higher pay.

Follow-up attrition affected the study at several junctures, but for the assessments considered here never exceeded 20%. Of the original 111 subjects, 105 were alive and eligible to take the several follow-up IQ assessments. At ages 2, 3, and 4, the number of subjects fully assessed on the Stanford-Binet IQ instrument were, respectively, 99, 98, and 99. At age 5, 95 children completed the assessment. At ages 6 ½ and 8, the number of children assessed dropped to 91. The age 12 and age 15 follow-ups saw the total number of children assessed rise to 101 and 104, respectively.

Independent Measures

Group Assignment. The main predictor of interest, group assignment, is a dichotomous variable where 0 denotes assignment to the control group and 1 denotes assignment to the experimental group.

Maternal IQ. In addition to the effect of treatment group assignment on children's cognitive outcomes, the main predictor of interest in the Carolina Abecedarian Project data, I also analyzed the effect of maternal IQ classification. I categorized the maternal IQ variable utilizing Herrnstein & Murray's (1994) definition of cognitive classes, with cut-points at the 5th, 25th, 75th, and 95th percentiles. The 5th percentile represents all those in the population with $IQ \leq 75$. Between the 5th and 25th percentiles is represented the 20 percent of the population who have IQs above 75, but below 91. Between the 25th and 75th percentiles is represented the middle 50 percent of the population who have IQs of at least 91, but no higher than 110. Between the 50th and 75th percentiles of the IQ distribution is represented 20 percent of the population who have IQs greater than 110 but lower than 120. Finally, five percent are represented in the distribution beyond the 95th percentile; these have IQs of 120 or greater. As none of the mothers in the data have IQs above the 75th percentile, the new variable is grouped into three categories representing the bottom 5 percent (mildly mental retarded), the 20 percent above it (borderline intellectual or low average), and the middle 50 percent (average).

Elucidating the difficulties experienced by those individuals in the bottom 5 percent of the IQ distribution, Gottfredson (1997) has noted that it is a very vulnerable class of citizens, often unable to meet the simple demands of a modern post-industrial

society. They are easily taken advantage of, suffer chronic unemployment, tend to live uneasy lives, and are more likely to live in poverty. As the economy changes and unskilled labor vanishes, people in this class become unemployable and are more prone to being on welfare long-term.

People who have IQs in the 76 to 90 range, although they are still quite vulnerable and have to fight an uphill battle just to make it in modern US society, at least have more job opportunities available to them, being slightly more trainable. This notwithstanding, these individuals experience a rate of poverty of about 16 percent, a rate of chronic welfare reciprocity of 17 percent, and a rate of school dropout of about 35 percent—all lower than the rates on the same variables experienced by those in the bottom 5 percent of the IQ distribution, but still disadvantageous.

The IQ range of 91 to 110, the highest range represented in the Carolina Abecedarian Project Data, corresponds to the middle 50 percent of the population. Gottfredson (1997) states that life is more secure for people in this range. Not only do they have lower rates of living in poverty (only 6%), of receiving welfare long-term (only 8%), and of school dropout (also only 6%), they are “readily trained for the bulk of jobs in society: clerks and secretaries, skilled trades and protective service workers, dispatchers, insurance sales representatives, and other midlevel work” (Gottfredson, 1997, p. 119). Even a high school dropout in this range of IQ is likely to meet the basic mental requirements for enlistment in the military, and all high school graduates do.

While break points along the IQ continuum can be arbitrary—with values at the higher end in a grouping not very different for life chances than the values at the lower end in the grouping above it—they do, as has just been demonstrated, have meaning for

the risks that the average person in a specific class faces with respect to the likelihood of experiencing poverty, poor academic performance, unemployment, and bad parenting (Herrnstein & Murray, 1994). Break points are also standard in professional practice and diagnoses of mental illnesses. According to standards set by the Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition, Text Revision (American Psychiatric Association [DSM-IV-TR], 2000), used by professional psychologists and psychiatrists, persons low in general intellectual functioning ($50 \leq IQ \leq 75$, taking into account measurement error), with attendant limitations in adaptive functioning, meet the definition of mild mental retardation. Along with very few moderately to profoundly mentally retarded persons, about 5 percent in the total population as stated above, or approximately 15 million people, fall into this class of being mildly mentally retarded. And while the children of people who fall into this class tend to be brighter than are their parents because of a regression to the mean in intelligence (Herrnstein & Murray, 1994), they are nonetheless at greater risk of suffering lower IQ scores (4 in 10 have IQs below 75; Gottfredson, 1997) according to many genetic behaviorists. Rutter, Simonoff, and Plomin (2008) highlight the fact, for instance, that mild mental retardation tends to run in families. If a child has one parent with mild mental retardation, he has a 20 percent chance of suffering mild mental retardation, while two parents with mild mental retardation increase this risk by another 22 percentage points to 42 percent. Plomin and Spinath (2004), in a review of the literature on genetics and intelligence, underscore the point that, while moderate to profound mental retardation does not seem to be shared among family members, mild mental retardation, on the other hand, does (see also Reed

& Reed, 1965). The average IQ for persons who had a mildly mentally retarded sibling, for instance, is 85.

Controls. To control for differences between the Stanford-Binet and Wechsler scales, I also included a dummy for the assessment instrument administered (Wechsler = 0, Stanford-Binet = 1). Assessment occasion (numbered 1, 2, ..., 8) was entered to account for changes occurring across time.

Data Analysis Plan

Because the impact of early education interventions have strong positive effects initially, followed by declines during adolescence, I employed the two-stage variant of the hierarchical linear model to conduct a quadratic growth model of age and children's IQ scores. At level one I sought to explicate the degree to which IQ scores change over time and whether such changes are attributable to other time-varying covariates. Distinct from standard regression techniques, in which covariates are treated as fixed, the effect of time-varying coefficients on child cognitive ability are allowed to vary across individuals in this model. Level two focuses on the between individual differences in IQ score outcomes by treating the intercepts and slopes at level one as outcomes.

Following the method analyzed in Raudenbush & Bryk (2002), I related individual growth in IQ test scores to the child's age, its quadratic, the specific assessment given, and whether treatment period was active or inactive. I then tested whether the effects of these variables varied across treatment group assignment and maternal IQ class. I first evaluated an unconditional quadratic growth curve model by estimating the following equations:

$$\text{Level one: IQ Score}_{it} = \pi_{0i} + \pi_{1i}(\text{age})_{it} + \pi_{2i}(\text{age}^2)_{it} + e_{it}$$

$$\text{Level two: } \pi_{0i} = \beta_{00} + u_{0i}, \quad \pi_{1i} = \beta_{10} + u_{1i}, \quad \pi_{2i} = \beta_{20} + u_{2i} \quad (4.1)$$

IQ Score is subscripted as it is assessed at time t for the i th individual among respondents. Age is entered so that it represents the IQ score measured at age 2, the initial age in the data used for analysis. The quadratic term is included to measure the acceleration in each growth trajectory. Viewing the random part of the level two models reveals that children are allowed to differ in their overall rate of growth and acceleration. I expected the level two coefficients to reveal significant variation across individuals with respect to mean IQ score, the mean rate of change in IQ score, and the mean acceleration in IQ score.

I next added the terms $\pi_{3i}(\text{Wechsler})$ and $\pi_{4i}(\text{post-treatment})$ to the level one equation, the first to control for differences between the Stanford-Binet and Wechsler IQ scales, and the second to control for differences arising from treatment period and post-treatment period. The third and fourth equations are added at level one and level two as shown in equation 4.2 below. Consistent with the extant literature on the Carolina Abecedarian Project, I anticipated that the coefficient for the Wechsler assessment would be slightly greater than Stanford-Binet while the coefficient for the post-treatment period would show a significant decline in IQ scores.

$$\begin{aligned} \text{Level one: IQ Score}_{it} = & \pi_{0i} + \pi_{1i}(\text{age})_{it} + \pi_{2i}(\text{age}^2)_{it} + \\ & \pi_{3i}(\text{Wechsler})_{it} + \pi_{4i}(\text{post-treatment})_{it} + e_{it} \end{aligned}$$

$$\begin{aligned} \text{Level two: } \pi_{0i} &= \beta_{00} + u_{0i}, & \pi_{1i} &= \beta_{10} + u_{1i}, & \pi_{2i} &= \beta_{20} + u_{2i} \\ \pi_{3i} &= \beta_{30}, & \pi_{4i} &= \beta_{40} \end{aligned} \quad (4.2)$$

To estimate whether treatment group assignment and mother's IQ class conditioned initial child IQ scores, the instantaneous rate of growth in child IQ scores, or the curvature in child IQ scores, I added these variables to the level two model. The level two equation assessing, for example, the slope of age on IQ score is represented in equation 4.3 below.

$$\begin{aligned} \text{Level two: } \pi_{1i} &= \beta_{10} + \beta_{11}(\text{treatment group})_i + \beta_{12}(\text{borderline maternal IQ})_i \\ &+ \beta_{13}(\text{mentally retarded maternal IQ})_i + u_{1i} \end{aligned} \quad (4.3)$$

Finally, I estimated a model that included at level two the two-way interaction between the two maternal IQ class and the treatment group dummy variables. Since I was primarily interested in the effect of treatment on the gains in IQ made by children of retarded IQ mothers, the coding for maternal IQ class was reversed in the final model. This allowed me to examine for whom the influence of the experimental preschool on both initial child IQ scores and on IQ scores measured over time was greatest: children of retarded IQ mothers, children of borderline/low average mothers, or children of average IQ mothers.

RESULTS

Descriptive Statistics

Descriptive analyses are presented in Tables 4.2 and 4.3. Table 4.2 shows, by maternal IQ classification, the control and treatment group mean IQs on the Stanford-Binet at 2, 3, and 4 years of age and on the Wechsler at 5, 6 ½, 8, 12, and 15 years of age. At every age, the mean IQ score of control group children whose mother had an IQ of 75 or less hovered between a low of 74 at age 3 and a high of about 83 at age 15, much lower than the mean scores of control group children of mothers in the two higher IQ classes. For example, the difference in mean IQ scores between the control group children of mothers in the highest IQ class and the control group children of mothers in the lowest IQ class approached almost 12 points at age 2, or nearly one standard deviation. At every age thereafter up to age 12, the difference in mean IQ scores between these two groups exceeds 15 IQ points. A similar picture emerges with respect to differences between control group children of low and midrange IQ mothers. In confirmation of the literature, a greater proportion of control group children of low IQ mothers, relative to their peers reared by higher IQ mothers, met the definition of being at-risk for developmental delay than is true of the entire sample of controlled subjects (never below 15%). While the proportion of control group children reared by low IQ mothers who could be classified as at least mildly mentally retarded ranged from 33% (at age 8) to 63% (at age 5), however, none of these had a score less than or equal to 75 by the age 15 follow-up.

[Table 4.2 About Here]

The near 12 point gap in IQ between control group children of the average and the retarded mothers at age 2, and the 9 point gap between control group children of the borderline/low average and retarded mothers at age 2, is not reflected in the differences in mean scores across maternal IQ class among treatment group children. Indeed, the mean IQ score of these children is identical in each of the three maternal IQ classes, standing at about 95, or a mere five points off the population mean IQ of 100. By age three, however, children reared by average IQ mothers show a mean IQ above 100, which is maintained up to age 15. The corresponding mean IQs of children reared by borderline/low average and retarded IQ mothers never breaks 100 and both fall to near 90 by age 15.

The discrepancy between control and treatment group mean IQs across the three maternal IQ classes reveals that the intervention was already showing a positive effect by age 2. The largest gains, though, were greatest for the most vulnerable children, i.e, those born to mentally retarded, poor, or at-risk, mothers. As Table 4.3 shows, the treatment effect for children of retarded mothers is greater than the treatment effect for children of borderline/low average and average mothers at all ages. Ranging from a high of 1.6 standard deviations to a low of .6 standard deviations, the difference in mean IQs between the control and treatment group children of low IQ mothers is statistically significant at all assessments. In contrast, the difference in mean IQs between the control and treatment group children of the borderline/low average IQ, and between the control and treatment group children of average IQ mothers, are statistically significant on the Stanford-Binet instrument only; no significant difference in mean performance was

shown to exist with respect to the Wechsler scales from age 5 to age 15 for children of either of these maternal IQ classes.

[Table 4.3 About Here]

Quadratic Growth Models

Table 4.4 presents the results of the quadratic growth curve models. The second column shows the null model that only includes the intercept. The average mean IQ over the several assessments is about 94, comfortably within the middle range of IQ in the population. The significant random effect reveals that there is a great degree of variation in the intercept of IQ scores across the project participants at age 2.

The unconditional quadratic growth model, shown in column 3, includes age and its squared term as covariates. The estimated age effect on IQ scores indicates an increase of 1.14 points from occasion to occasion. The coefficient representing the curvature suggests, however, that, over time, the instantaneous linear growth rate decelerates. The random effects for both instantaneous growth and curvature imply highly variable slopes such that those above the mean on initial IQ score experience a greater increase in scores from year to year, with an attendant slower deceleration, and those below the mean on initial IQ score experience a smaller increase in scores from year to year, with an attendant faster deceleration.

The third model, shown in column 4, includes Wechsler and post-treatment period as time-varying covariates at level one. The results confirm previous findings showing a general decline in IQ scores after the treatment period ends, i.e., after age 5, and higher

scores on the Wechsler scales of intelligence relative to the Stanford-Binet scales. These statistically significant results are net of the effects due to age and acceleration.

Column 5 presents the intercepts- and slopes-as-outcomes model. Here, the predictors at level two, treatment group and maternal IQ class, are both hypothesized to have differential impacts on the slope of initial status, age, and curvature. The first thing to note is that both treatment group assignment and maternal IQ class have an independent effect on child IQ scores at age 2. That is, while all the treated children experienced a positive effect from the intervention, there was a significant difference in this effect when the additive influence of children's mothers' IQ class was taken into account. With respect to standardized IQ scores, for example, it was the children of average and borderline/low average IQ mothers, compared to children of retarded mothers, who performed best. The trajectory of scores shown in the equations for growth rate (π_{1i}) and acceleration (π_{2i}) revealed that, while the control group children in each of the three maternal IQ classes grew on the measure of IQ at a faster rate than their treated peers, they also experienced faster deceleration in their scores over time. That untreated children should be growing at a faster rate than their treated peers likely stems from the fact that, since gains from intervention are already operative by age 2, the treated children, having benefitted from intervention, have less room to make gains. Indeed, compared to the maternal IQ-specific trajectories of IQ scores for the control group children, the corresponding trajectories for the treatment group children appear to be pretty flat. The treatment group children of borderline/low average and average maternal IQ mothers make small gains from occasion to occasion. Not unlike their untreated counterparts, however, these gains tend to reverse themselves, already bending the

trajectory downwards before the children reach adolescence. Interestingly, the treatment group children of retarded mothers trend first downwards in their IQ growth, but their loss due to age slows such that the curvature in their trajectory is inclining upwards by adolescence.

[Table 4.4 About Here]

Figure 4.1 displays a graphical representation of the equation implied in model 4 of Table 4.4. The expected quadratic growth in IQ scores increases slightly among the treatment group children of borderline/low average and average IQ mothers, but eventually scores drop off very dramatically. The corresponding trajectory of the treatment group children of retarded mothers is already declining at age 2, but, given that the rate of growth is close enough to zero and the rate of acceleration is significantly positive, it begins, by the final assessment, to turn upward. It is apparent from this that the gains from intervention have a greater lasting effect on the children of retarded mothers. By age 15 treatment group children of retarded mothers are performing about the same as control group children of borderline/low average IQ mothers. Given the upward trend for the IQ trajectories of treated children of low IQ mothers and the downward trend for the IQ trajectories of treated children of higher IQ mothers, it is not unreasonable to predict the three groups eventually arriving at a mean IQ score that is statistically identical. If we return to Table 4.2, for instance, we already see a trend that seems to confirm this conjecture. Note the small or shrinking differences, by age 15, in

treatment group mean IQs among children of retarded IQ mothers (IQ = 92),
borderline/low average IQ mothers (IQ = 94), and average IQ mothers (IQ = 100).

[Figure 4.1 About Here]

The final model shown in the last column of Table 4.4 adds the interaction between treatment group and maternal IQ class to the level two equations for the slope of initial status, growth rate, and acceleration. Because the analysis here is focused on the gains from treatment achieved by the children of the retarded IQ mothers, the coding for maternal IQ class is reversed; hence, the main effects coefficient for treatment represents the difference in IQ score between the control group children and their treatment group counterparts when the maternal IQ class equals zero (i.e., when it references the retarded maternal IQ class) and the interactions represent the difference of the difference, or the difference in the treatment effect between children of retarded IQ and borderline/low average IQ mothers, and between children of retarded IQ and average IQ mothers. While the results reveal no significant relationship between the relevant interactions and either age or its quadratic, the impact on initial status is striking. Significant at the .001 level, the treatment effect for children of retarded mothers is on the order of 22 IQ points, or almost 1.5 standard deviations, at age 2. Contrastingly, the distance between the control and treatment group mean IQ for children of borderline/low average and average mothers, significant at the .05 level, was about half this value, or .75 standard deviations.

CONCLUSION

Environments matter with respect to long-term life chances, especially in the early years. The good environments provided by loving parents who actively engage and stimulate the cognitive growth of their young children are preferred to the abject environments of parents who provide the opposite. Likely as important, however, are the heritable traits and predispositions children receive from their parents, which have consequences for how children react to, or act on, the environmental stimuli they encounter throughout the life course. This paper provides evidence that the effect of the Carolina Abecedarian Project's intense preschool intervention—a radical augmentation to the environment than would otherwise have been experienced by the at-risk children studied—depends on the level of maternal IQ. The treatment effect was greatest for those born into the most vulnerable circumstances, i.e., those born to parents with IQs in the mild mental retardation range of 50 to 75, when taking into account measurement error. This is most apparent at the age-2 assessment, during which the treated children of retarded IQ mothers outperformed their control counterparts by about 20 points. The corresponding gaps among the treated children of borderline/low average and average mothers were, respectively, about 10 and 8 points, considerably less than the figure for children of low IQ mothers.

The trajectory of scores suggests, too, that the treated children of the low IQ mothers experienced lasting gains over their treated counterparts reared by higher IQ moms, who saw their scores drop off precipitously by age 15. Certainly, while inconsequential differences in mean IQ scores were found to exist between treatment and control group children of the two highest maternal IQ classes at the age 15 follow-up, the

difference in mean IQ score between treatment and control group children of low IQ mothers was a statistically significant 9 points, or approximately .7 standard deviations. A substantial separation on its face alone, this difference in mean IQ scores is also the difference of being classified as low average intelligence (controls) versus average intelligence (treatment).

Given the results of this paper, the relevant question is whether early childhood education interventions are the answer to gaps in cognitive ability and learning so persistent at all ages in the United States. It may indeed be more cost-effective in the long run if early education interventions were focused on the subgroup of poor children from families where one or both parents have low IQ. Such an intervention, of course, would likely need to span the period prior to formal schooling into late adolescence, and it would necessarily need to be the same high quality and consistency of the Carolina Abecedarian Project. Drawing from the results of one study, however impressive, may be not enough. Wachs (1999), highlighting the multi-determined nature of child development, states that where interventions are concerned, 1) it is important to avoid the assumption that one type will be a cure-all, 2) policy makers should not expect what has worked in one context to work in all contexts, 3) the design of the interventions cannot focus on a single outcome, and 4) it is vital to know before implementation of such programs what behavioral and familial issues are prone to interfere with whatever gains are initially observed. Wachs (1999) argues that only “multi-level repeated” and targeted interventions that take full measure of existing developmental issues are worth the effort.

It should be remembered that, although the Carolina Abecedarian Project and a few longitudinal randomized trials like it have attempted to be multifocal and were

undoubtedly of high quality, they were always done on a small scale, did not deal with all aspects of child development at all stages of growth, and tended to focus mainly on IQ or achievement gains (with the focus on gains in other domains after the programs ended mainly seen as byproducts of these). As such, policy makers can only construe their findings to be nothing other than context specific. A first next step, which ought to take into account the preceding points, and which would meet the standard advocated by Wachs, would be to replicate the Carolina Abecedarian Project on a larger scale. A similar trial targeting both urban and rural locations across the different regions of the country could serve as a better guide for future policy recommendations.

Table 4.1. Intra- and intergenerational correlation coefficients between personal characteristics and socioeconomic outcomes averaged from four studies analyzed by Jencks et al., 1979.

	Father's Occupation	Son's			
		IQ	Education	Occupation	Earnings
Father					
Education	.48	.27	.40	.28	.20
Occupation		.29	.38	.31	.22
Son					
IQ			.57	.46	.28
Education				.61	.38
Occupation					.43

Source: "Intelligence and Social Inequality: Why the Biological Link?" by Linda Gottfredson, Table 20.1, p. 539, in *The Wiley-Blackwell Handbook of Individual Differences*, First Edition. Copyright © 2011 by Blackwell Publishing Ltd.

Table 4.2. Means on Stanford-Binet and Wechsler instruments by age of assessment, maternal IQ class, and group assignment.

IQ Instrument and age given	Maternal IQ ≤ 75				Maternal IQ between 76 & 90				Maternal IQ ≥ 91			
	Control		Treatment		Control		Treatment		Control		Treatment	
	<i>n</i>	<i>M</i>	<i>n</i>	<i>M</i>	<i>n</i>	<i>M</i>	<i>n</i>	<i>M</i>	<i>n</i>	<i>M</i>	<i>n</i>	<i>M</i>
Stanford-Binet - age 2	8	76.75	9	95.33	30	85.77	25	95.64	10	88.30	17	96.00
Stanford-Binet - age 3	8	74.00	9	98.44	30	85.10	25	98.52	10	91.30	16	104.81
Stanford-Binet - age 4	8	75.75	9	98.78	29	90.66	25	99.08	10	96.70	16	106.00
WPPSI - age 5	7	79.29	9	98.44	29	95.14	24	99.25	10	101.20	16	106.06
WISC-R - age 6 1/2	6	75.17	8	95.00	29	94.03	23	95.65	9	99.33	16	104.91
WISC-R - age 8	6	80.92	9	93.78	29	95.41	24	96.13	9	97.88	15	104.90
WISC-R - age 12	6	77.00	9	90.33	32	88.34	25	92.64	11	96.64	18	99.72
WISC-R - age 15	7	82.71	9	91.89	32	91.06	25	93.60	12	95.00	19	99.79

Table 4.3. *p*-values from Student's *t*, testing equality of means between control and treated subjects in each maternal IQ class.

IQ Instrument and age given	Maternal IQ ≤ 75			Maternal IQ between 76 & 90			Maternal IQ between 91 & 110	
	Diff. in means	<i>p</i> -val		Diff. in means	<i>p</i> -val		Diff. in means	<i>p</i> -val
Stanford-Binet - age 2	18.6	0.0002	***	9.9	0.0003	***	7.7	0.1000
Stanford-Binet - age 3	24.4	0.0001	***	13.4	0.0005	***	13.5	0.0206 *
Stanford-Binet - age 4	23.0	0.0003	***	8.4	0.0079	**	9.3	0.0365 *
WPPSI - age 5	19.2	0.0049	**	4.1	0.1786		4.9	0.3107
WISC-R - age 6.5	19.8	0.0014	**	1.6	0.5463		5.6	0.2749
WISC-R - age 8	12.9	0.0362	*	0.7	0.8139		4.9	0.3943
WISC-R - age 12	13.3	0.0132	*	4.3	0.0750		3.1	0.4326
WISC-R - age 15	9.2	0.0354	*	2.5	0.3509		4.8	0.1857

The difference in means column is an effect of treatment and control group responses at a given test and age by maternal IQ class. The *t*-statistic refers to the observed values against which the simulated *t*'s are compared. *** $p < .001$, ** $p < .01$, * $p < .05$.

Table 4. 4. Quadratic growth curve model of child IQ scores.

Predictor	Model 1: Intercept only model	Model 2: Unconditional quadratic growth model	Model 3: Wechsler scale and treatment period	Model 4: Level two covariates (treatment group and maternal IQ class)	Model 5: Level two interactions
Fixed Effects:					
Initial Status, π_{0i}					
Intercept, β_{00}	93.99 (0.99)***	92.40 (1.26)***	91.82 (1.21)***	87.41 (2.52)***	75.21 (1.99)***
Treatment, β_{01}				13.54 (2.09)***	22.32 (3.08)***
Borderline/low average IQ mother, β_{02}				-2.49 (2.66)	
Mildly mentally retarded IQ mother, β_{03}				-7.59 (2.92)*	
Borderline/low average IQ mother, β_{02}					10.32 (2.63)***
Average IQ mother, β_{03}					14.02 (3.92)***
Treatment x Borderline IQ, β_{04}					-10.15 (4.18)*
Treatment x Average IQ, β_{05}					-11.67 (5.40)*
Growth rate, π_{1i}					
Intercept, β_{10}		1.14 (0.27)***	1.42 (0.42)***	3.43 (0.73)***	0.54 (1.10)
Treatment, β_{11}				-1.88 (0.52)***	-0.90 (1.25)
Borderline/low average IQ mother, β_{12}				-1.20 (0.66)	
Mildly mentally retarded IQ mother, β_{13}				-2.32 (0.83)**	
Borderline/low average IQ mother, β_{12}					1.90 (1.07)
Average IQ mother, β_{13}					2.63 (1.47)
Treatment x Borderline IQ, β_{14}					-1.44 (1.39)
Treatment x Average IQ, β_{15}					-0.56 (1.75)

Acceleration, π_{2i}					
Intercept, β_{20}		-0.09 (0.02)***	-0.10 (.03)***	-0.22 (0.05)***	0.01 (0.07)
Treatment, β_{21}				0.09 (0.03)**	-0.01 (0.09)
Borderline/low average IQ mother, β_{22}				0.08 (0.04)	
Mildly mentally retarded IQ mother, β_{23}				0.17 (0.06)**	
Borderline/low average IQ mother, β_{22}					-0.17 (0.07)*
Average IQ mother, β_{23}					-0.22 (0.10)*
Treatment x Borderline IQ, β_{24}					0.14 (0.10)
Treatment x Average IQ, β_{25}					0.09 (0.12)
Wechsler, π_{3i}					
Intercept, β_{30}			2.56 (0.98)**	2.56 (0.98)**	2.55 (0.98)**
Post-treatment, π_{4i}					
Intercept, β_{40}			-4.23 (0.90) ***	-4.22 (0.90)***	-4.23 (0.90)***
Random Effects:					
Intercept, π_{0i}	9.85***	11.77***	11.77***	9.27***	9.05***
Growth rate, π_{1i}		1.90***	1.92***	1.58***	1.56***
Acceleration, π_{2i}		0.10**	0.09**	0.08*	0.07*
Level 1 error, e_{ii}	7.56	6.35	6.22	6.18	6.18
Deviance	5614.24	5495.30	5471.44	5409.08	5401.23

The bolded coefficients in the leftmost column denote changes in the coding of the maternal IQ classes and refer only to model 5 in the table, which includes interaction terms. Wechsler is a dummy variable denoting the psychometric test administered; it is coded 0 for Stanford-Binet (taken at ages 2, 3, and 4) and 1 for Wechsler (taken from age 5 to 15). Post-treatment is a dummy variable coded 0 for treatment period and 1 for post-treatment period. Treatment is coded 1 for treatment group and 0 for control group. Borderline/low average IQ mother and mildly mentally retarded IQ mother are dummies whose reference category is average IQ mother. Parenthetical values refer the standard errors of the estimates.

*p < .05, **p < .01, ***p < .001.

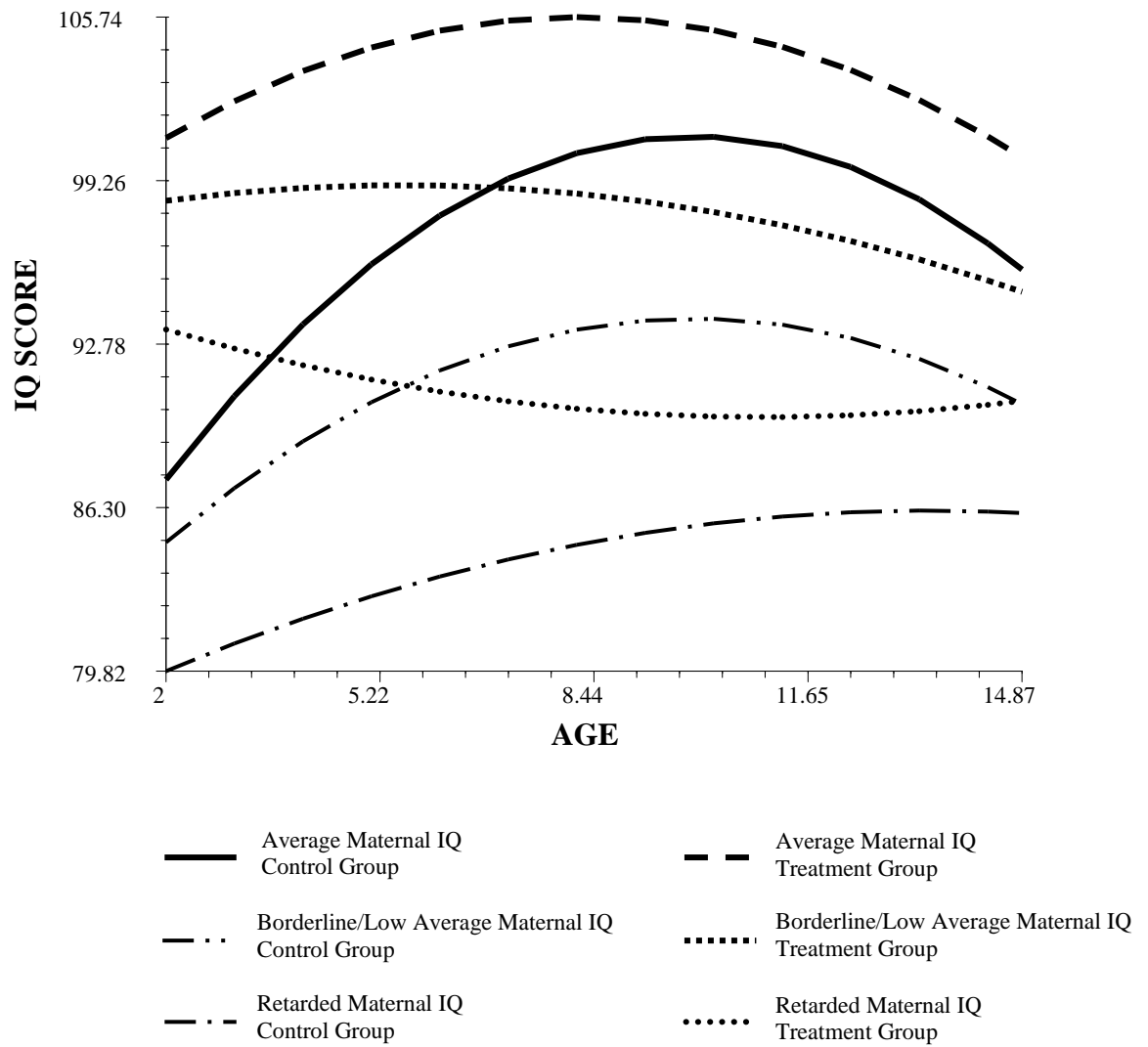


Figure 4.1. Child IQ Score × Age × Maternal IQ × Group Assignment.

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CHAPTER 5

CONCLUSION: CONDITIONS FOR EFFECTIVE KNOWLEDGE ACQUISITION

With an eye focused on sharpening theory and perhaps lending support to specific policy prescriptions, this dissertation examined, roughly, the ways in which parental skill attainment influences children's cognitive growth and development. Each of three separate but related essays considered whether and how the path from parents' abilities to child outcomes might vary according to the particular measure of attainment, a specific child outcome, a certain policy designed to achieve parity, or some combination of at least two of these. In the first study (Chapter 2), trajectories of mathematics and reading comprehension were assessed with respect to their dependence on a child's mother's age at first birth, net of the effects of other direct measures of skills attainment. Whereas the existing literature has tended to utilize inadequate methods to assess growth, my approach made up for this shortcoming by making use of hierarchical linear modeling. The second study (Chapter 3), which took a psychometric measure of maternal intelligence and treated it as a proximal determinant of children's academic achievement, sought to explicate the degree to which its indirect effect via family socioeconomic status (SES) was conditional on the level of maternal intelligence itself. Finally, the third study (Chapter 4) attempted to uncover whether the results of a well-known early childhood randomized intervention trial indicated treatment effect heterogeneity by maternal

intelligence. The importance of these findings to possible policy prescriptions is discussed below.

Early Maternal Age and Child Academic Outcomes

Investigating the effect of early maternal age on children's mathematics and reading comprehension performance revealed two truths. First, controlling for several background factors of women, as well as controlling for present household factors, there is definitely a negative impact on children's academic growth of having a mother who began childbearing prior to age 20. Second, the extent of this negative effect, in addition to varying across the specific outcomes analyzed, can vary as a function of time or age. We see this most interesting fact clearly in the case of the mathematics percentile scores, where the effect of early maternal age, while nonexistent at school entry, is related to those disparities in outcomes resulting from the passage of time.

That early child-bearers perform significantly less well on specific measures of skill attainment such as education and the Armed Forces Qualification Test (AFQT) percentile score, and that there exists a significant impact of early maternal age on children's outcomes after accounting for these factors, certainly supports the idea that early maternal age is a good proxy for skill attainment over and above that provided by such measures. The importance of this finding to racial and class disparities is evident in the results presented in Tables 2.2 and 2.3. Regarding mathematics performance, black and Hispanic children and children from poorer backgrounds fare the worst at school entry, and they do not really improve thereafter. There is no real difference between the races on reading comprehension at age 7, but the class background of the mothers of

these children is still a very salient predictor. And while reading comprehension tends to slacken with age for all children, the trend is worse for black and Hispanic children. Both blacks and Hispanics are also more likely to begin childbearing before adulthood.

None of this is to suggest that delaying childbearing will close the achievement gap. That would be naïve. But the perfect need no be the enemy of the good. Delaying childbearing is a start to closing the racial and class achievement gap for the obvious reason that it allows young women the opportunity to improve skill attainment in the other areas of their lives. To be sure, some delayers may not progress any further than they would if they had had a child, but the fact that they do not have a child could at least mean less experience with financial difficulties for themselves and less strain on social safety nets to assist the poor or their children.

Conditional Indirect Effects of Maternal Intelligence

Diverse literatures often point to different determinants of child outcomes. In the social sciences, a typical predictor studied is SES. In behavioral genetics, it is genotypes or phenotypes of innate abilities such as intelligence that are of utmost interest. Going beyond the nature-nurture debate that has raged within the social sciences over the past couple of decades, I investigated how both phenotypic maternal intelligence (measured on the AFQT) and SES, working together, impact children's academic performance. To the degree that individuals' intelligence indicates their innate ability it precedes SES temporally. I treated it as such in my analysis.

Controlling for age, gender, and race, SES as a mediator of the maternal intelligence-child academic outcomes relationship was shown to have a decreasing effect

as the level of maternal intelligence improved. That is, children reared in low IQ homes benefitted most from increases to SES while children from higher IQ homes benefitted somewhat less from the same increases. Does this mean that in-kind transfers can close the achievement gap? The answer to that question is probably not, or at least not a lot. Increased money with no attendant gains to parental education and job prestige could possibly help those children raised in the most destitute circumstances. Indeed, in preliminary analysis of these data that focused on family income rather than SES, this was actually shown to be the case. But those children reared in middle IQ homes would reap no benefits. Whereas the mediating impact of family income alone had a ceiling at about the 35th percentile of maternal AFQT on only two of the measures studied, the mediating impact of SES was present at pretty much the entire range of maternal AFQT on all four measures studied. It appears that when it comes to improving children's life chances, there are indeed things that money cannot buy. Whatever are the cultural gains to improvements to educational attainment and job prestige, they are certainly just as important to children's academic performance as is money, and perhaps more so.

Early Education Intervention and Treatment Effect Differences

Recent years have seen the advancement of a number of arguments in favor of preschool education, many of them based on the results of randomized trials. While the call from some corners has advocated universal education prior to age 5, others have maintained that targeting the most vulnerable children is, in the long-run, probably more attainable and cost-efficient. From the research done here, it is clear that early and intense childhood interventions do indeed possess some promise for disadvantaged populations.

Interestingly, while all children seemed to benefit from treatment group assignment, though, the results indicated that the most disadvantaged youngsters (i.e., those whose mother had an IQ score on the Wechsler scale in the mildly mentally retarded range from 50 – 75) showed the largest gains over their control group counterparts. It is true that these children did not score as high in raw percentile scores as their peers reared by higher IQ mothers, but neither did they see the rapid declines, or disappearing effect, of treatment as a function of time. Instead, rather than rising quickly and dropping thereafter in their trajectory as children of poor mothers of moderate and average IQ, from age 2 on the trajectory of IQ scores of children of mothers who were both poor and low IQ trended downwards then upwards.

The results of this study seem to indicate that it is probably best as a policy position to focus like a laser on improving, or supplementing, the environments of poor children known to be reared by parents of depressed IQ. The results do not necessarily preclude broader coverage, but broader coverage implies larger costs. And if the benefit is more heavily weighted toward children of low IQ parents over all other children, such costs, and hence broader coverage, may not be warranted. To be sure, given that the data in this study are composed primarily of disadvantaged black Americans in a small college town, the results may not be representative. It may be worth it to replicate the study on a larger scale to buttress what has been found here. Axiomatically, though, all policymakers would agree that an optimized environment is a necessary condition to optimizing learning. If low IQ, poor parents are less likely to provide expectable environments for their children, it makes sense to address environmental deficiencies when they are identified.

Concluding Thoughts

The determinants of academic growth and development are a mix of social and biological factors. Social consequences of families deriving from deficiencies to the biological barriers can, if they are applied accurately, forestall cognitive delay and failure. This finding provides good information for how to close the achievement gap in learning, which, given the change in demographics to take place over the next generation, will become a greater concern than it presently is. Since in the next generation the size of the black and Hispanic populations will continue to increase and together exceed the size of the white population, tendencies within those populations toward early pregnancy and childbirth will likely have a greater negative impact on the sustainability of the welfare state. As such, it is in the national interest to stem early pregnancy and birth. This is easier said than done, however.

Trends toward general decline in the positive cultural habits that once characterized the majority of Americans, even those from minority groups, have been resistant to attempts to reverse them. Indeed, the changing landscape of black communities due to middle-class flight and self-segregation from the poor that accompanied the civil rights successes of the 1950s and 1960s (Wilson, 1987) has been replicated in “white America” (Murray, 2012). The result, now as twenty-five years ago, is an urban underclass free of the constraining influence of middle-class American values that once used to filter down to them as an upshot of close proximity. Both Wilson and Murray have argued that some of this state of affairs is a consequence of the general refusal of scholars and policymakers alike to criticize the behaviors of the underclass out of fear of being viewed as blaming the victims. Whatever benefits the professional gains

from this approach, it has contributed nothing to assisting the so-called victims to appropriate habits that might change their deplorable conditions.

More forceful and frequent efforts must be made to address, perhaps in the form of public service announcements, the deleterious effects of early childbearing. It disrupts the life course of young women and puts added stress on already overextended social service agencies. Beyond stemming teen pregnancy and birth, policy should focus on increasing skill attainment at all levels of education. If standards have fallen over the past generation, they ought to be raised again; more must be expected of students. Since family life plays a big role in knowledge acquisition, increasing the skill level of low-income parents is a necessary adjunct to any in-kind transfers. This recognition that often the most vulnerable children aren't just poor, but also the offspring of low cognitive ability parents, should figure in efforts at early education intervention. Ultimately, closing the racial and class achievement gap will require looking beyond race and class and accepting hard truths and employing tough programs to address them directly.

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