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Does Increased Family Income Reduce Fade Out of Preschool Gains?

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DOES INCREASED FAMILY INCOME REDUCE FADE OUT OF PRESCHOOL GAINS?

A Dissertation Presented

by

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ABSTRACT

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The current study examines the connection between a change of family income and the retention of academic gains for children in low-income households who have attended a center-based preschool program. These children are often shown to lose the academic advantage they gain during preschool as they move through k-12 education in a phenomenon called fade out. A theoretical framework was constructed positing that material and psychological effects of poverty inhibit the ability of these families to support and maintain growth during this critical time when children are highly nested in the family unit.

Treating family income as a causal risk factor, a study was crafted to examine the fade out effect when family income increased during early childhood for children in low-income households. Using the ECLS-K data set, ex post facto, quasi-experimental methods were employed to analyze two comparison groups of low-income children who went through a center-based preschool program. One group gained the treatment of a constant increase in family income beginning during early childhood (LIP), while the other stayed within their starting low-income bracket throughout the study (LCP). Multiple regression analysis was used to test if this treatment would correlate to the LIP group retaining more of their preschool skills than the LCP group, measuring from kindergarten to eighth grade. Before the main dependent cognitive measures (math and reading scores) were examined, regressions on social competence variables were performed. After examination, these variables were added as controls to the academic regressions.

The results of the academic regressions showed that the LIP group correlated to nearly a one-half reduction in fade out as compared to the LCP group by eighth grade in both mathematics and reading. These findings lead to many implications for researchers, practitioners, and policy makers as well as open the door to future exploration into the subject.

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CHAPTER I

OVERVIEW

There are many issues surrounding education in America but none bigger at this point in history than the achievement gap. Ever since the Civil Rights movement of the 1960s, researchers have been struggling to try to find solutions. During that time, a change of philosophy occurred in society from a social Darwinian view that intelligence was static and that those who were behind in school were born without the capacity to do well, to an environmentalist view. Through scientific study, researchers were able to illustrate that intelligence was far from inert and that environmental factors were a variable in how intelligent a child was measured to be (Heckman, 2008; Kagan, 2002).

Ever since then, there has been an ongoing debate on how to prevent and alleviate environmental factors that cause learning gaps. This is especially true when examining the plight of at-risk children, as poverty and low parental education seem to accelerate these gaps (Duncan, Ludwig, & Magnuson, 2007; Kagan, 2002). As studies have dug deeper into early childhood learning and consensus has been reached that much learning takes place before formal schooling begins, a glaring problem exists. Those children who are of low socioeconomic status and/or belong to a racial minority often enter schools far behind their white middle class counterparts. The achievement gap for poor students starts well before formal schooling (Barnett, Camilli, Ryan, & Vargas, 2010; Magnuson & Shager, 2010).

With this awareness comes the devastating research that these gaps in school knowledge get worse as children grow older. Gaps in achievement widen through school years and children caught on the wrong side are much more likely to end up in special education, repeat grades, and ultimately drop out of school (Barnett, et al., 2010; Belfield, Nores, Barnett, & Schweinhart, 2006; Karoly, Kilburn, & Cannon, 2005). These early educational gaps eventually hinder an individual's ability to succeed socially and economically in mainstream American society.

A hot button issue surrounding this discussion is early childhood education. Head Start and other center-based preschool programs have attempted to address some of the educational inequities for poor children. Early childhood education has been shown to help shrink the educational gap for low-income and minority children (Belfield, et al., 2006; Karoly, et al., 2005). Although programs and services of these preschool intervention programs are quite varied, research highlights certain ideal activities (Barnett, et al., 2010; Durlak, 2003; Karoly, et al., 2005). And though children attending quality preschool intervention programs show gains in school readiness and overall life outcomes as compared to their peers in poverty, much of the tangible educational gains are lost as poor children move through k-12 education and the gaps between these students and their middle class counterparts expand (Magnuson & Shager, 2010).

An outside factor surrounding preschool programs is the issue of family resources. The more capital (human, social, financial) a child's family has, the better outcomes are as he or she moves into formal schooling (Coleman, 1988). For poor families, an increase of income at this time has been linked to gains in educational outcomes for children (Heckman, 2008). And though gains are relatively small, they seem to be sustained throughout school (Gennetian, Castells, & Morris, 2010). How a change in family income connects and interacts with the long-term effectiveness of early intervention programs is of particular interest in the upcoming study.

Context and Rationale

I began my work in education as a literacy teacher at the Suffolk County House of Corrections in Boston, Massachusetts. The majority of my student inmates were black or Hispanic/ Latino males from working-class neighborhoods in Boston. Many were young and had very few mainstream educational skills. Worse was the lack of hope that their aspirations in legitimate society could be fulfilled. Many were caught in a never-ending cycle between dealings in the illicit market (drugs, prostitution, etc.) and the prison system. Although many could see and understand the cycle, they felt powerless to change their trajectory and make it in legitimate society, especially without the skills valued in that realm.

My next educational destination was the Boston Public Schools to see if I could help to curb this pattern. As a middle school teacher in a predominately black, working-class neighborhood, I could already see the demoralizing effects of the achievement gap by the sixth grade. Students in regular education classrooms were frequently performing well below grade level. Many had already lost hope and ambition in school. Those who did have drive still faced a mountain of formidable educational challenges on top of their family's economic struggles. These characteristics were all too similar to those in the house of correction, leading me to believe many of my current students were potential future inmate students. This fear has come to fruition numerous times in my still young (eight years) public school teaching career.

In my subsequent readings, I have been able to trace many of these students' struggles all the way back to the womb. Children from more enriched environments, at least as it relates to the current educational system, enter school better prepared than their counterparts of low socioeconomic status (SES). Longitudinal data from sources such as the Early Childhood Longitudinal Study – Kindergarten Class of 1998-1999 (ECLS-K) illustrate that these differences get larger throughout the course of a k-12 education. According to the United States Department of Education, in 2011 48% of fourth graders who were eligible for free or reduced lunch scored less that a basic level of reading on the NAEP test. For those not eligible, only 18% fail to reach this measure. Moreover, the percentage of students eligible for free or reduced lunch has grown every collection year, from 38% in 1998 to 48% in 2011 (National Center for Education Statistics, 2011). Any county, state, or national statistics on both high school dropout and incarceration rates paint bleak pictures for at-risk populations.

Early childhood interventions are a way to try to stop gaps before they start. Evidence suggests that early learning is the foundation for all subsequent learning (Barnett, et al., 2010; Belfield, et al., 2006; Karoly, et al., 2005), and numerous studies have shown a link between preschool attendance and high school completion (Clements, Reynolds, & Hickey, 2004).

This topic is extremely important in the current political and educational environments as both the governor of Massachusetts, Deval Patrick, and President Obama have extensive early childhood spending plans. Of particular interest to policy makers and urban educational leaders should be those aspects in and around preschool programs that are linked with positive results for individuals and society, maximizing the investment.

One factor that has been shown to improve student achievement during the formative ages in a child's life, independent of preschool, is increased family income, especially when increases are consistent. Numerous natural and true experimental programs during welfare reform of the mid-1990s have created a strong base for this claim (Gennetian, et al., 2010).

With the onset of No Child Left Behind in the Bush era and programs such as Race to the Top in the Obama administration, policy leaders seem to argue that education is the country's major anti-poverty program. Examining the interaction between increase of income for families in poverty and its affect on preschool intervention programming's long-term effectiveness may implore some of these same leaders to also look at the inverse relationship, namely, anti-poverty programs and policies as a way of improving education for poor children.

Definitions

- Preschool: For the purpose of discussion, "preschool" will have the characteristics of being center-based, starting before k-12 education, and concentrating on the cognitive development of children (Barnett, et al., 2010; Clements, et al., 2004).
- Young Children/ Early Childhood: Young children and early childhood will be interchangeable and the National Association for the Education of Young Children (NAEYC) definition will be used to describe these children as under the age of 8 (NAEYC).

- Preschool gains: Preschool gains will be defined as higher levels of cognitive and/or social/emotional performance upon entering kindergarten (school readiness) for children who attended center-based preschool when compared to peers with similar demographics, family structures, economic status and numerous other variables who did not attend a center-based preschool
- Fade out of gains: Fade out of preschool gains will be defined as the lessening of higher cognitive and/or social/emotional performance in school by those who went through a center-based preschool as compared to their peers who did not attend a center-based preschool as time passes from kindergarten.

Theoretical Framework

The basis of my study is rooted in a few major theories in education and child development. I merely introduce them here:

Risk factor theory.

Risk Factor Theory posits that we should only be concerned with those factors that can be changed and show improvement for children. Other fixed and variable factors can flag those who are at-risk but are not worth the effort of trying to change because either they cannot be changed or they have not been proven to affect the education of at-risk children.

Bourdieuian capital theory.

This theory posits that society revolves around three main types of capital (economic, cultural, and social), which are used to gain legitimate power in a society. These three types of capital are interchangeable, meaning one can be converted or traded for another.

An example would be parents using economic capital to hire a tutor so that their child could gain more cultural capital in the form of more school knowledge.

Bronfenbrenner's ecological theory of child development.

This theory maintains that many layers of environmental systems have affects on children directly and indirectly. Most young children's proximal processes (primary engines of development) are within the family. Since young children are closely nested to parents and the family, they are more sensitive to changes within the family. Yet, change is less overwhelming for young children as they are mostly dealing solely within the family environment and developmentally adapt to change. This contrasts with older adolescents who are dealing with complex changes both biologically and in relation to other systems in society. Thus, the theory supports early childhood as an appropriate and unique time for family change to affect children positively.

My theoretical framework- layering the three theories.

The Risk Factor theory combined with Bourdieuian capital theory creates a frame in which family socioeconomics is a major risk factor that can affect a child's success in school. This is a departure from most users of risk factor theory in preschool studies who usually treat socioeconomic factors as a marker (a factor used to identify). Thus, this lens gives credence to viewing both center-based preschool and a positive change in income status as ways to build and maintain the capital needed to perform better in school. Layered with ecological theory, these changes in family income are best suited to make the strongest effects on children during early childhood.

Research Questions

How does a significant and steady increase in family income in low-income families during early childhood affect the fade out of academic gains from preschool programs through grade school?

How does a significant and steady increase in family income in poor families during early childhood affect the fade out of social gains from preschool programs through grade school?

Study Design

The nature of my study was a quasi-experimental longitudinal analysis using the Early Childhood Longitudinal Survey – Kindergarten Cohort (ECLS-K) as a data source. Using an untreated control group design with dependent pretest and posttest samples, I created two baseline/reference groups and two comparison groups for least squares dummy variable multiple regressions.

The two comparison groups (LCP and LIP) in the study both included children from low-income families who attended a center-based preschool program before kindergarten. The difference between the groups was that the LIP group experienced a significant and long lasting increase in family income between kindergarten and first grade (experimental group), and the LCP group's family income stayed consistently low through the study (control group). These two groups were compared to a middle income reference group (MICB) and a low-income, no preschool baseline group (LCNPB) to examine to what extent the LIP and LCP groups' cognitive skills and social competence faded since kindergarten. The hypothesis was that the LIP group would exhibit less fade out than the LCP group as compared to the middle income and low-income, no preschool reference groups.

Study Results:

The results from the least squares dummy variable multiple regressions supported the study's hypothesis for cognitive skills. Both math and reading regressions from kindergarten through eighth grade illustrated a pattern where the LCP and LIP groups faded at two different rates away from the MICB and towards the LCNPB group in successive collection years. Holding all background variables equal, the LIP group had around half of the fade out as compared to the LCP group by the end of eighth grade. This supported the hypothesis that an influx in income early in childhood helped to preserve the gains these children from low-income families made in preschool.

Limitations and Implications:

Of the major limitations of the study, generalizability and applicability across subsets of the populations are the most glaring. Because the nature of the study, ex post facto, participants were not selected randomly. Although there are robust controls, all non-random studies increase the probability for type II error when applied to other population outside the current cohort of students. Also, since the study focused strictly on low-income children, claims for other income levels cannot be made via the research. Moreover, the inability to run separate regressions on different subgroups of low-income students (e.g. race) leaves out the ability to differentiate between more exclusive groups.

Despite these limitations, the study has major implications for researchers, practitioners, and policy makers. Researchers should reconsider their use of income as a marker variable (static) and shift to a lens in which income is a causal risk variable (fluid). Practitioners should consider adding programming in their settings that would support a higher family income during the early childhood of their students. Policy makers should support universal policies that would help low-income families, especially those with young children, become upwardly mobile for the long-term.

Preschool programming has shown the ability to affect educational and life outcomes for children born in poverty. Increases in family income in early childhood have also been shown to improve educational outcomes slightly but sustained over time. The examination of the interaction between these two factors in poor children's lives offers a way to combat the fade out of skills gained in preschool, affecting the overall socioeconomic achievement gap in schools.

CHAPTER II

REVIEW OF THEORIES AND LITERATURE

Theoretical Framework: Basis for a Study of Preschool and Family Economic Status

Supporters of preschool intervention programs assume that early learning is foundational and that these programs can help change risk factors in at-risk children's lives. This view intertwined with cultural capital/ social reproduction theory and ecological theory illustrates a unique opportunity to change the life trajectory of low-income children early in life.

Risk Factor Theory.

Risk Factor Theory states that there are three types of risk for at-risk children: fixed factors, variable markers, and causal risk factors. A fixed factor is a risk that cannot be changed (i.e. race). A variable marker can be changed but has not been shown to alter the negative educational outcomes for poor children. An example of a variable marker for at-risk children could be housing. A program could help move families from older housing projects to newer ones. However, this would not be a wise focus of a preschool intervention program since there is no evidence that this would change the probability of at-risk children's educational attainment. A causal risk factor can be changed and does alter the risk for poor children. An example of a causal risk factor would be parental involvement. Research has shown when programs get parents involved at higher levels children perform better in school (Karoly, et al., 2005; Lee, 2010). Fixed factors and variable markers are more suited to identify those who are at risk, but interventions should be concentrated on causal risk factors since they can mediate risk for low-income children (Huffman, et al., 2001; Karoly, et al., 2005).

Capital and Social Reproduction Theory.

Bourdieu (1986) theorizes that society works through gaining and maintaining capital. In our current capitalistic society, power lies in three main types of capital: economic (money), cultural (understanding of dominate knowledge and working of dominant culture), and social (title, nobility, and relationships). Once an individual gains one of these types of capital, he or she can convert it to one or both of the other types. Since cultural capital is mainly gained by investing time to gather knowledge and skills valued by the dominant class, it can be an entry point for any child in society to eventually obtain legitimate power. While their middle class counterparts accumulate the cultural capital to adhere and take advantage of school through transmission in their upbringing, low-income students often arrive with subjugated forms of cultural capital, usually leaving them ill-prepared for institutional goals and norms. They lack the dominant cultural capital needed to prosper in schools, which prevents them from gaining social capital in the form of good grades, associations with key groups, and diplomas. The lack of social capital and credentials often leaves those from low-income backgrounds with little means to gain economic capital in the *legitimate* economic system (Bourdieu, 1986).

This interaction of societal structures and capital tends to reproduce class disparity, perpetuating the cycle of those starting in lower classes retaining their subjugated positions. This is the crux of Social Reproduction Theory. Current status quo societal conditions keep the rich prosperous and the poor marginalized. This process is legitimized through our current system of schooling (MacLeod, 1995; Swartz, 1997), where upper and middle class knowledge is school knowledge; putting those in the upper classes at a formative advantage and leading to diplomas that are to be viewed as the objective justification for who is and who is not successful in society.

The interaction of these theories presents an interesting and fairly complementary framework, with Bourdieuian theory shifting the focal point. Theory on cultural capital layers well with risk factor theory in interpreting the school struggles of poor children. However, most prior users of risk factor theory in educational research describe socio-economic status as a marker variable (one that cannot be changed) (Karoly, et al., 2005). This suggests that there is a strict boundary between the field of education and other fields such as policy and economics. In contrast, if we take Bourdieu's outlook on fields and the different types of capital, there are no such fixed boundaries. With this lens, the fields of policy, economics, and education infringe on one another due to the ability to exchange capital and therefore have the potential to influence each other. By treating socioeconomic status as a marker variable, much of the prior preschool research has failed to fully develop the possible interaction between family economics and preschool intervention programs.

Bronfenbrenner's Ecological Systems Theory.

Ecological Systems Theory states that there are five layered environmental systems that affect an individual's development: the micro-system, meso-system, exo-system, macro-system, and chrono-system. All systems have effects on an individual's development either directly or indirectly. A person lives and is an active contributor in the micro-system, which includes his or her most direct contact. Examples of micro-systems would be the family, peer relationships, and school. The meso-system is the relationship between different micro-systems and the effects that experiences in one will have on another. The exo-system involves environments in which an individual has no direct control over and describes these environments' relationship to his or her immediate context. An example of this would be the media's negative portrayals of Muslims and how its effects trickle down to an individual Muslim's development. The macro-system is the overarching cultural values and beliefs in society and the chrono-system are changes in the environment or transitions over time. All these layers have effects on the development of an individual (Bronfenbrenner, 1979).

Using the lens of Ecological Systems Theory, changing a family characteristic should be most effective during early childhood age. At this stage of life, most of children's proximal processes, interaction that produces human development, are highly nested in the family micro-system. In turn, positive or negative family changes during early formative years will have a stronger effect than at older ages when children are directly interacting with more environments and micro-systems in society (Bronfenbrenner & Morris, 1998). In other words, for young children, most of everything is mediated through the family unit. The outside world has little to no direct effect on them. But changes in their parents' lives and resources (exo-system) will have major indirect effects on their development.

Theoretical Framework.

Taking the theoretical framework for Risk Factor and capital theory in combination with ecological theory suggests that helping to address a family's economic status while attending to the cognitive and social effects of being born in poverty during early developmental years should lead to higher, sustained school performance and better life outcomes.

As previously stated, preschool can help foster cultural capital that low-income children lack. Introducing family economics into the equation, economic capital can be traded for cultural capital. For example, with more money a working-class family could pay for an intensive tutoring program for their children to obtain cultural capital and ultimately gain social capital (i.e. connections with elites, high school diploma, college degree). Those credentials could then be used to gain access to the legitimate economic system. In addition to buying cultural capital, seeing parental success in the economic system could improve a poor child's aspiration through shifting his or her habitus. Habitus is the attitudes, beliefs, and disposition of an individual based on his or her social world (Bourdieu, 1986; MacLeod, 1995). Poor children live in a world where few people, including family members, are successful in the mainstream economy. This is internalized and added to a child's habitus, seeing his or her future as a low-level worker and thus devaluing school. This outlook in combination with the structural inequalities in society tends to reproduce the current social structures (MacLeod, 1995). Seeing a parent succeed in the economic system may help to shift the habitus of a child, encouraging higher aspirations, which could positively affect his or her investment in school.

Additionally, low-income parents who are able to access the middle class job market may increase their cultural and social capital, which could in turn affect the choices they make for their children. Access and entry into such workforces could stave off the isolation that often comes with poverty, a key component of social reproduction, and expose parents to other forms of knowledge valued in the upper and middle classes (Anyon, 2005).

The ability of families to continue to trade and gain economic and cultural capital throughout a poor child's school career may be an important means to slow or stop the fade out of preschool growth as children move through grade school. In addition, this frame gains theoretical support from Bronfenbrenner, co-founder of Head Start, whose ecological theory points at early childhood age as the most opportune to time to implement both preschool and income increases. These theories layered together suggest a unique opportunity to enhance the change in trajectory of children's education when coordinated with a change in family economic trajectory.

Review of Preschool Intervention Program Research

Supporters of preschool intervention programs assume that early learning is foundational and that these programs can help change factors in at-risk children's lives. The Cumulative Learning Theory posits that latter school learning is based on early childhood development. As Karolyn, Kilburn, and Cannon (2005) state, "Evidence suggests that early learning is cumulative and that basic early childhood skills are a necessary foundation for learning other skills in school" (p. 20). Teaching fundamental skills pertinent to success in k-12 schools as early as possible will improve outcomes in school. This is especially important for low-income students, whose home environments often give them limited access to the middle-class knowledge necessary for school success.

Preschool aged children and poverty.

Much of the achievement gaps, including gaps between races, in representative nationwide data are closely related to poverty differences (Duncan & Magnuson, 2005). For instance, when examining the ECLS-K both the cognitive test scores and the socio-economic profile of black children were around two-thirds of a standard deviation behind their white peers (Duncan, et al., 2007). Much of those differences can be traced to the historical inequalities for racial minorities in America. The past nature versus nurture debate over intelligence and success is obsolete today. Modern research has shown that although there may be differences in what is inherited, ability is largely created and that the environment, even in the womb, affects how genetic ability is manifested (Rutter, 2006). In other words, ability is not inert or simply inherited. Therefore, past research linking inherited cognitive levels with social class in the absence of environmental discussions is flawed and misleading. It can be said that much of cognitive ability is contingent on a child's environment.

When it comes to home environment for preschoolers, there is much difference between the haves and have-nots in the country. In line with the Cumulative Learning Theory, neuroscience has shown that complex cognitive capabilities are built on cognitive skills gained during early childhood. These early skills are sensitive to experiences in young childhood (Duncan, et al., 2007; Knudsen, Heckman, Cameron, & Shonkoff, 2006). Yet the environments that children grow-up in differ greatly among the classes. Children in families in the top fifth income level are four times as likely to have a computer in the home and on average have three times as many books as do the lowest fifth in income level in the country. In contrast, children in the bottom fifth are read to less often, are more likely to watch television, and gain about half as much vocabulary from their parents as do the upper fifth (Duncan, et al., 2007).

All these differences create gaps in school readiness between the classes. School readiness usually refers to skills in preschool aged students such as letter and number recognition, as well as behavioral factors such as sitting still and following directions (Duncan, et al., 2007; Magnuson & Shager, 2010). Children from poor backgrounds and racial minorities score nearly 0.65 of a standard deviation in reading and 0.75 of a standard deviation in math behind their white middle class peers upon entering kindergarten. This is estimated to be nearly six months behind in school years (Duncan & Magnuson, 2005). Students who score poorly on cognitive tests in their preschool years are more likely to be teen parents, dropouts, and become unemployed adults (Rouse, Brooks-Gunn, & McLanahan, 2005).

Poverty has been also shown to have negative social/emotional effects on young children. More aggressive physical behavior entering kindergarten is associated not only with poorer cognitive scores but also higher rates of criminal activity when older (Duncan, et al., 2007). Researchers have been able to show that such problem behaviors are distinctly higher in children in poverty as early as 17 months of age (Duncan, et al., 2007).

Preschool and the lowest-income children.

Numerous studies have found that the biggest gains in preschool intervention programs have been by children in the most chronically or desperately poor families

(Currie & Thomas, 1995; Magnuson & Shager, 2010). These researchers suggest that poor preschoolers have the most to gain from the educationally enriching environment of preschool intervention programs, since they are the least likely to get it at home or in their neighborhoods. For example, in populations that are overly represented in poverty statistics, such as African Americans and Hispanics, researchers have found that mothers tend to read less to their children, stunting language development by age three (Raikes, et al., 2006). Puma's (2006) national study showed that these same subgroups benefited the most from Head Start programs, showing the highest gain in preschool scores. Puma's follow-up study in 2010 showed that the highest risk sub-group had the most sustained gains by the end of preschool (Puma, 2010).

Despite the fact that preschool intervention seems so important to poor children's development, only 60% of poor children (the lowest quartile in terms of SES) attend any type of preschool and even less are enrolled in effective preschool intervention programs (Magnuson & Shager, 2010).

Effective preschool sites.

Although not the focus of this review, it is important to note that there are differences in the quality of center-based preschool programs. If investments by society are made in preschool programs, they need to be as effective as possible in bridging gaps for disadvantaged children upon entering k-12 schooling and beyond. Despite research on program-wide success, individual aspects and services of these preschool intervention programs are quite varied, making it hard to conclude to which aspects they owe their success (Durlak, 2003; Karoly, et al., 2005). However, some important elements of preschool intervention programs are supported by research, especially inside the preschool classroom. These elements include: small class size (Barnett, Camilli, Ryan, & Vargas, 2010), both direct and inquiry based instructional practices (Nelson, Westhues, & MacLeod, 2003; Stipek & Byler, 2004; Stipek, et al., 1998), teacher training (Cassidy, Hestenes, Hegde, Hestenes, & Mims, 2005), teacher retention (Castro, Bryant, Peisner-Feinberg, & Skinner, 2004; Whitebook & Sakai, 2003), engaging parents at multiple levels (Brookes, Summers, Thornburg, Ispa, & Lane, 2006; Lee, 2010; Puma, 2010; Raikes, et al., 2006), and higher levels of per-pupil expenditure, including wrap-around services (Currie & Neidell, 2007; Duncan, Ludwig, & Magnuson, 2007; Heckman, 2008; Magnuson & Shager, 2010).

Preschool intervention evaluated by experimental design.

The bulk of cited research studies evaluating the success of preschool intervention programs have been experimental or quasi-experimental in nature. A few classic experimental studies (Belfield, et al., 2006; Clements, et al., 2004; Masse & Barnett, 2002) are highly cited in the study of early childhood intervention. However, because of the moral dilemma of not giving children potentially life-altering services, quasi-experimental methods are used very often to compare two similar groups of children (Barnett, et al., 2010; Belfield, et al., 2006; Duncan, et al., 2007; Karoly, et al., 2005). A typical piece of research evaluation at the program level would have children in a program compared to children of a similar background who are not able to receive services due to lack of availability. When researching a specific aspect of a program, often, differing programs servicing similar populations are compared for an outcome.

One exemplar research program created to study the effects of early intervention programs is the Chicago Longitudinal Study. This experiment, which started in the early

1980’s, compared children from Chicago’s inner-city who went through an extensive early childhood education program (n=989) against their peers in the same cohort, selected randomly (n=550), who did not participate in the program. The creators developed a comprehensive data set from birth to age 24 with reports from the families, schools, administrators, and other sources of information. Over the past 20 years numerous studies and follow-ups on this cohort of children have examined such aspects as school performance disparities, social well-being comparisons, and the cost effectiveness of the program (Reynolds & Ou, 2010).

Preschool’s long-term effects.

Most major meta-analyses and longitudinal studies of center-based preschool programs show long-term gains from childhood to adulthood (Barnett, et al., 2010; Karoly, et al., 2005; Ou, 2005). These benefits include less grade retention, fewer behavioral problems, reduced dropout rates, higher employment, and lower rates of incarceration. For example, Garces, Thomas, and Currie (2002) used the Panel Survey of Income Dynamics (PSID), a nationally representative longitudinal survey of around 4500 families and 18000 individuals, in combination with supplementary early childhood questions for the 1995 survey to look at long-term effects of Head Start. These researchers linked lower incarceration rates for African Americans and decreased dropout and grade retention for whites with Head Start attendance. Joo (2010) used this same data to find that in chronically poor families, Head Start was associated with higher cognitive scores and fewer behavioral problems in school for poor black females.

Some of the most powerful research within the study of center-based preschool’s longer-term effects is cost/benefit analysis. Cost/benefit analysis compares the dollar amount spent on a preschool program against the measureable longitudinal benefits in the form of discounted dollars (discounted for inflation and other factors). To measure the benefits, those who went through a program are compared to a similar or random group that did not get the preschool treatment. At different snapshots in time, the two groups are compared in terms of their costs/contributions to society and personal outcomes. The discounted difference between the two groups, divided by the amount spent on the preschool treatment would give a cost/benefit dollar ratio (Barnett, et al., 2010). The most rigorous studies show not only improvement for individual life outcomes for low-income children (less prison, more earnings) but also, net returns of $1.26 to $17.07 per dollar spent to society (Barnett, et al., 2010; Belfield, et al., 2006).

Maybe the most famous of these cost/benefit experiments is the Perry Preschool Program. The study, cited by major supporter of early childhood education including Head Start, randomly selected children for an intensive preschool program (n=58) and a control group of children (n=65) from an impoverished area in Michigan during the 1960's. The program group received center based preschool, home visits, and parent group meetings for one or two academic years. Examining costs (school retention, welfare, incarceration) and benefits (tax collection due to employment) for society, the latest follow-up studies (40 years after) show that every dollar invested in the program yielded 6.5 dollars in benefit as compared to the control group. Benefits for individuals ranged from around 50,000 to 18,000 dollars in lifetime earning depending on the discount rate used by the researchers (Belfield, et al., 2006).

It is important to note that the Perry program and experimental programs like it spend much more money per pupil than normal Head Start or other center-based preschool programs frequented by low-income children (Currie & Neidell, 2007; Duncan, et al., 2007). This more expensive model may show better long-term results than other programs due to the amount of extra-supports given outside the family. This is important to remember as the discussion turns to the fade out of preschool skills.

Effects of fade out in school.

Although research suggests longer-term life benefits for individuals in preschool intervention programs, one major concern about early childhood education is the fade out effect, or the fading of preschool cognitive and social-emotional gains in children as they move through k-12 education. Fade out is usually portrayed in low-income and racial minority groups and linked to lower quality school and home environments throughout formal schooling. Researchers Lee & Loeb (1995) used National Education Longitudinal Study (NELS) data to link fade out to poor quality grade schools for those who went through center-based preschool programs. Currie & Thomas (1995) also found that fade out is quickest with low-income urban minorties. They attribute this mainly to poor quality grade schools and home environments as compared to their white counterparts who show more long-term school gains.

Long-term school gains from preschool programs are assumed to be linked with family support (Lee, 2010; Reynolds & Ou, 2010). For example, using NLSY data, Lee (2010) found that black children who attend Head Start had better long-term educational results when Home Observation for Measurement of the Environment (HOME) scores were higher. Part of Reynolds and Ou's (2010) research review on the long-term effects of the Chicago Longitudinal Study examined the relationship between home environment and long-term success of preschool participants. They found that those participants in families with higher human capital and family functioning measures as well as those whose family profile positively changed before adolescence had higher educational attainment.

Despite any gains found in preschool, family background (SES level, home environment) persist as the biggest factor for whether students achieve in the long run (Joo, 2010). And, it is suggested that in order to keep gains long-term, children need to be in environments that continually support their development (Foster, et al., 2005; Reynolds, 1998). As Lee, 2010 states, "The most common explanation for the long-term benefits of Head Start are the reciprocal interactions between children's cognitive gains and family support even after the child exits the program" p. 324. This suggests that parental life trajectory may impact the long-term educational trajectory of children.

Review of Family Socioeconomic Status and Achievement

One way to examine the ability to support gains in preschool is the capability of the home to provide an enriching environment both with tangible resources and emotional support. Engles and Black (2008) state:

> In addition to providing basic necessities, such as food, shelter, and clothes, families transmit cultural and educational values and help children adapt to societal demands and opportunities. Early parent– child interactions help children learn regulatory process and socialize them into the rhythm of their family and culture. p. 245

Socioeconomic status (SES) can have a great effect on parents' ability to provide and the quality of what is provided. It is believed that no policy can affect all parts of SES.

However, based on the research, income may be an aspect of SES better targeted for change (Gennetian, et al., 2010).

Income as a measure of socioeconomic status.

There are many different ways to measures what researchers consider to be socioeconomic status (SES). One major approach is to aggregate multiple measures, such as occupation, income, and family education level into one variable called SES. More recently, researchers are examining the differing factors of SES separately, believing that they have differing effects on families (Hauser & Warren, 1997). Duncan and Magnuson (2005) consider this multi-dimensional lens as more in line with the research, particularly describing income, family education, family structure, and neighborhood profile as the main measures of socioeconomic status. Examining all of these variables, interventions affecting income shows the most promise for children in school.

A change in parental education level is very difficult to link to increased student achievement. As Duncan and Magnuson (2005) state, “few studies are able to disentangle parents' schooling from other sources of advantage, such as cognitive endowments, that may have increased achievement among both parents and children” p. 41. Although parental education level has been linked to cognitive test scores, interventions that try to increase parental educational levels have had very few positive effects (Duncan & Magnuson, 2005; Roth, Brooks-Gunn, Murray, & Foster, 1998).

Family structure is another important factor in socioeconomic status. Nearly 50% of children living with single mothers are in poverty, compared to 10% of those living in intact families (Duncan & Magnuson, 2005). On average, children in single parent households have lower levels of educational and social well-being. This is especially true for those of teen mothers, who also tend to be of lower SES status.

Although family structure has been link to academic and social performance, when family background is accounted for, researchers only note modest negative effects with being raised in a single family or divorced household (Duncan & Magnuson, 2005). Much of these effects are caused by financial hardship. Furthermore, even if a program could create more marriages and less divorce, researchers believe that it would still have to go hand in hand with an increase in financial resources to see any measurable gains in a child's social and cognitive outcomes (Duncan & Magnuson, 2005).

Neighborhoods are also a factor usually entered into socioeconomic status. In poor, especially urban, neighborhoods stress from violence and drug activity may negatively affect children. The lack of positive role models and strong community structures such as police protection and adequate schools may cause children to exhibit behaviors that are detrimental to school performance (Duncan, et al., 2007; Massey, 1998).

Despite the problems poor neighborhoods cause for children, dealing with neighborhood status in isolation has not been proven to be successful. A study conducted by Leventhal, Fauth and Brooks-Gunn (2005) illustrates this point. These researchers reexamined an earlier study that relocated poor families from a high poverty area to a low poverty area. While there were some initial gains in school achievement, these researchers found that five years later the children in these families were actually performing worse than those who stayed in high poverty areas. While there are plenty of possible explanations for the regression in progress, the main factor remained that economic levels for the families never changed (Leventhal, Fauth, & Brooks-Gunn, 2005). This example shows how complex it is to try to intervene in such contextual elements such as neighborhood index. As Duncan and Magnuson (2005) state, "Interventions focused exclusively on neighborhoods rather than on influences directly related to the child, family, and school cannot solve the myriad problems of children growing up in high-poverty urban neighborhoods" p. 45.

Much of the differences in family structure, parental human capital, and neighborhoods can be tied to family economics, which in most cases is attached to parent income. Higher levels of income can be linked to more resources, better health care, and an overall enriching environment for children. In addition, economic improvement has shown stronger effects on poor children than on middle class and wealthy children (Magnuson & Shager, 2010). In fact, the lack of an enriching environment has been blamed for a major portion of poverty effects in children (Duncan, et al., 2007). Accounting for all the factors in SES, if interventions were to be made in socio-economic status, income seems to be the most logical place since it appears to influence all other factors of SES. Researchers have surmised, of all aspects, increasing income for poor families could significantly reduce achievement gaps (Duncan & Magnuson, 2005).

Theoretical groundings for income effects.

Income has two major theoretical effects on children's educational attainment. One strand of effects is mediated by the psychological well-being of the family. As far back as the 1970s, it has been theorized that low-income has damaging effects on adult heads of families that trickle down to the children (Elder, 1974). Stress leads to depression, which affects parenting and support for children's school endeavors (Yeung, Linver, & Brooks-Gunn, 2002). More recent research has linked low-income families to higher rates of depression as measure by such tools as the HOME scale. These higher rates of depression amongst parents were then linked to low levels of achievement in children, especially when examining problem behaviors (Chase-Lansdale & Pittman, 2002; Morris, Duncan, & Clark-Kauffman, 2005; Yeung, et al., 2002). The second effect income has on children is mediated by the ability of a family to create an enriching environment. The more money a family has, the more they can then support an enriching educational environment including items such as books and activities such as museum trips (Morris, et al., 2005; Yeung, et al., 2002).

Yeung, Linver, and Brooks-Gunn (2002) hypothesized that these two mediating streams would have differing outcomes on low-income children. The researchers felt that the physically enriched environment would be linked to higher cognitive scores. Stress and depression levels, which they call the family process measure, would be correlated with behavior measures. Indeed, higher cognitive test scores on the Woodcock Johnson III were link to the ability to invest in an educational environment, while income was mediated through family stress and depression levels when looking at children's Behavior Problem Index (BPI).

Although the two theoretical streams may seem to mediate income's effects on children differently, researchers warn not to completely separate the two as they may affect each other (Magnuson & Shager, 2010; Yeung, et al., 2002). For instance, increased income may affect the stress levels of a single mother, which in turn may ease depression, which may lead to more quality involvement in the education of the child including purchasing books and trips to a museum, which is part of creating an enriching environment.

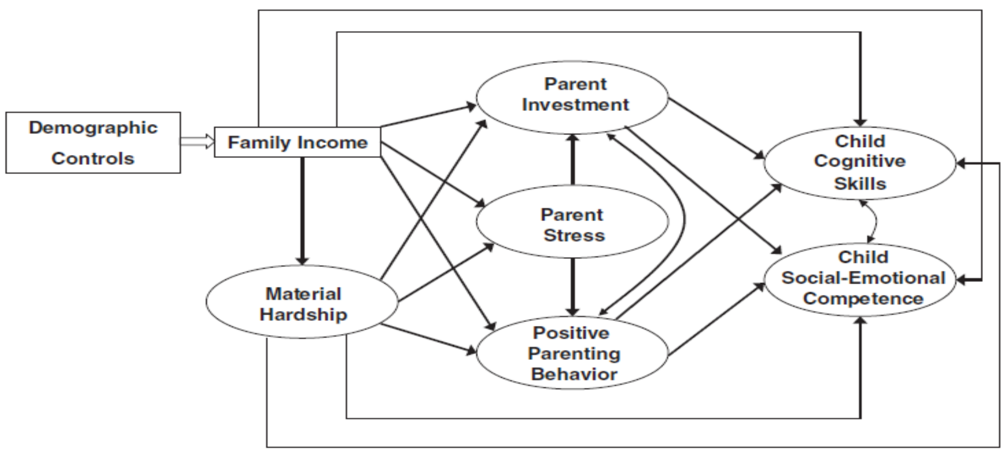
Much of Colman's (1988) theory on the interaction between financial, human, and social capital can augment this view of interplay between physical and psychological effects of parental income on children. He discusses them stating,

> Financial capital is approximately measured by the family's wealth or income. It provides the physical resources that can aid achievement: a fixed place in the home for studying, materials to aid learning, the financial resources that smooth family problems…Human capital is approximately measured by parents' education and provides the potential for a cognitive environment for the child that aids learning…The social capital of the family is the relations between children and parents (and, when families include other members, relationships with them as well)… if the human capital possessed by parents is not complemented by social capital embodied in family relations, it is irrelevant to the child's educational growth that the parent has a great deal, or a small amount, of human capital. p.109-110

In other words, social capital (presence and attention) allows for human capital (skills and knowledge) to be used in a family to help support children. One of the biggest challenges in low-income homes is fighting against low attention and expectations due to depression, multiple children, and single parent environments. So low-income households are usually not only lower in financial and human capital but also, the vehicle to use these types of capital, social capital, often is broken by the psychological toll of poverty on parents.

Income's paths through the family to affect child outcomes are well summed conceptually by Gershoff, Aber, Raver, and Lennon (2007), built much on the above work of Yeung, Linver, and Brooks-Gunn (2002). These researchers use the Early Childhood Longitudinal Survey (ECLS) to both test a construct they call "material hardship" and to see how this construct and income are mediated through the family to affect young children's cognitive skills and social-emotional competence.

Figure 1: Mediated and Direct Effects of Income (Gershoff et al., 2007)



Income intervention in early childhood.

It is believed that the most developmentally appropriate time to target the income of poor families is during early childhood. First, it is thought that the negative effects of low-income are reversible in young children since these children are not entrenched in poverty (Morris, et al., 2005). Also, children are perceived to be more malleable at these ages then when compared to stages such as transitioning into adolescence (Gennetian, et al., 2010). This may be due to the fact that transitioning to adolescence is a stressful time where more change in the family may be a detriment (Ge, Lorenz, Conger, Elder, & Simons, 1994; Morris, et al., 2005; Shonkoff & Phillips, 2000). Researchers also suggest that because young children are nested in their families, increased family income and employment are more effective than in different stages in life (Bronfenbrenner & Morris, 1998; Brooks-Gunn, Han, & Waldfogel, 2002).

Numerous studies using sophisticated instruments support early childhood as the most effective time to increase parental income of children in poverty (Brooks-Gunn, et al., 2002; Gennetian, et al., 2010; Gennetian & Miller, 2002; Huston, et al., 2001; Morris, et al., 2005; Zaslow, et al., 2002). Zaslow, et al. (2002) illustrate that increases in income may have negative school effects, behavior, and academic performance, in older children. Studying ten different programs across the country directed at moving mothers from welfare to work, the researchers found consistent negative effects on cognitive and behavioral measures across studies when examining adolescent children in these families. The researchers point to erosion of parenting and supervision and an increase in adolescent responsibility due to new job placements as possible reasons for these trends. This combined with the stresses many behavioral scientists note in adolescents illuminate why this time period in a child's life may show signs of strain when parental work is introduced (Gennetian et al., 2002).

More research points to keeping the interventions until at least after the first several months after birth. Work before this point may be too early due to maternal/child separation issues (Baydar & Brooksgunn, 1991; Brooks-Gunn, et al., 2002; P. Morris, et al., 2005). A well-cited study that illustrates this point is Baydar and Brooks-Gunn (1991). These researchers studied a sample of 3 and 4 year-old children (n=1181) from the National Longitudinal Survey of Youth (NLYS) 1986. Looking at the current cognitive testing for the children, they linked childcare type, maternal vs. non-maternal, and test scores based on the year the mother entered the work force (year 1, 2, or 3). The results showed that entering the workforce during a child's first year was significantly detrimental to his or her cognitive test scores at 3 and 4 years of age, accounting for all other variances. But, those mothers who entered during the second and third years of life, showed no negative effects on cognitive performance. All of the signs in the research point to early childhood as an appropriate time for income and employment intervention, starting a year after birth.

Evolution of income policy research.

Income's effects on children have been a highly researched topic since the anti-poverty policies in the 1960's under President Lyndon Johnson (Gennetian, et al., 2010). Since then, child poverty rates have ebbed and flowed, currently sitting at around 17% or 13 million children who live under the official threshold for poverty. The percentage jumps when examining minorities, as 35% of Blacks and nearly 30% of Hispanic children live under the poverty line. This number is rising due to the economic down turn the country has taken since 2008 (Gennetian, et al., 2010).

Welfare reform programs of the mid-1990's have been credited with decreasing the amount of families in poverty; although some argue that the booming job market in the early 2000's may have had a big role (Gennetian, et al., 2010). Many of these welfare reform programs have pushed welfare to work. But, the problem of income is not just a problem of unemployment. Nearly 80% of children who are labeled low-income come from families with at least one parent that works and 55% with at least one parent who works full time (Fass and Cauthen, 2007; Gennetian, et al., 2010). And without the federal and state Earned Income Tax Credit (EITC) nearly 10 million more people, including 5 million more children, would live under the poverty line (CBPP, 2013).

Researchers have noted that welfare policies have had differing effects on children's early achievement. Those programs that push women into jobs with long hours have been shown to have negative effects on child development when compared to those designed for women to work less than full-time (Loeb, Fuller, Kagan, & Carrol, 2003; Zaslow & Emig, 1997; Zaslow, et al., 2002). In addition, many welfare-to-work programs do not increase a family's overall income. So, parents are not home to support their child's learning and have little more economic capital to show for it.

Because of the above research and the fact that other variables between SES levels are difficult to control, much of the research on policy surrounding socioeconomic status examines change in income level as a main variable. Some of the first sophisticated models examining effects of income showed little to no benefit to children when income was increased and other family variables were controlled (Blau, 1999) (Shea, 2000). The problem with these studies is that they used data sets with diverse income levels. When looking specifically at low-income families, other researchers began to find significant effects when income was increased. Zaslow et al. (2002) study on ten welfare programs concludes that children of families in incentivized welfare-to-work programs, where earnings were higher than welfare benefits, increased early learning and cognitive growth into elementary school. Moreover, the impact of such welfare programs were most positively linked to those families who were higher risk, or those that have been on welfare for extended periods or generations (Zaslow, et al., 2002). Many studies used fixed assignment in an experimental design, while other relied on natural experiments. With these different designs came differing effect sizes, many with fairly high returns for every $1000 increase in annual earnings (Gennetian & Miller, 2002; Huston, et al., 2001; Morris & Gennetian, 2003).

A limitation with these, noted in the research of Morris and Gennetian (2003), is that they fail to account for other variables introduced when income levels are increased, namely, the effect of being employed. These researchers took these previous methods one step further by accounting for employment variables in their design. The researchers studied an experimental welfare reform program in Minnesota aimed at increasing income as well as putting families in poverty to work. Because some participants were only given employment at welfare-level income and others were given incentives which increased their income, the researchers were able to study three groups: those with no treatment (control), those that were given work without an income increase, and those that were given both work and monetary incentives to boost income. Measuring effects of work and income level, they were able to conclude that just being employed had no significant effect on children's academic or behavior measures, but being employed with a higher income did show increased performance in behavior and school engagement, with an increase of $1000 in annual salary improving child performance on test scores by a quarter of a standard deviation. Although these results seem exaggerated and lack wide-ranging generalizability when compared to more extensive and contemporary studies, this approach led to many other studies of income and education.

More recently, other research has shown a smaller but significant increase in child performance when income is increased (Gennetian, et al., 2010). Morris, Duncan, and

Kauffman (2005) evaluated 13 experimental welfare-to-work programs created during welfare reform in the mid-1990s. They concentrated on two specific types of programming: welfare-to-work programs that aimed to increase income and welfare to work programs that focused on work requirements and punitive measure. Using complex regression models, these researchers were able to illustrate that those programs that increased income showed higher gains for children in early elementary school by around .10 of a standard deviation as compared to control groups.

Although the effect size measures in most contemporary income research seem fairly small, even little achievement gains result in better life outcomes. If even a .07 standard deviation change in performance were permanent, it could increase future earning on average by around 15,000 dollars (Krueger, 2003; Morris, et al., 2005).

Effects of long-term income increase.

A major issue surrounding reforms such as welfare-to-work programs are that they are often inconsistent and short-term (Duncan, et al., 2007; Gennetian, et al., 2010; Meyer & Sullivan, 2004). Such interventions do not allow for families to continue supporting their young ones as they move through grade school.

A few studies can illustrate the differing impacts of short-term and long-term income increases. Huston et al. (2001) studied the New Hope program, an antipoverty program that increased parental income for multiple years. After five years, children measured the same positive gains on cognitive and social tests as they did in the baseline year. This may be due to the consistent level of support families were receiving. Dahl and Lockner (2008) conducted a study that illustrates the impact of both short-term and long-term income increases. They used changes in the EITC to examine the effects of variation in household income on children's math and English language arts scores. Their findings showed that a $1000 increase to annual family income was correlated to a 6% standard deviation increase in combined math and English scores. This was even more dramatic for the lowest income families. However if this income was not sustained, gains quickly disappeared. In addition to student performance yo-yoing from inconstant aid, these changes can psychologically damage parents. Yeung et al. (2002) describes a study in which a 30 % negative change in income is linked to higher rates of depression and punitive parenting which, as discussed prior, can trickle down to children and affect school performance.

These studies suggest that it may be very important to have consistent aid or employment in order for income increases to continually support student performance both socially and academically. For this, steady employment may be the better option as government programs and policies both are often inconsistent and nondiscretionary for parents (Magnuson & Shager, 2010). For example, many government welfare-to-work programs are not long-term and only boost a mother's income 1000 to 2000 dollars per year, which is not even close to enough to close the earnings gap between whites and at-risk minorities, the rich and the poor (Duncan & Magnuson, 2005). If educational gains due to increased income are to take root for young children in poverty, significant and steady increases are necessary.

Limited Preschool and Income Combined Studies

As Lee (2010) posits, "Past Head Start evaluations have not examined the developmental trajectories of children's outcomes in the context of trajectories of parental outcomes" p 324. In other words, research has examined the trajectory of children due to preschool, but has yet to examine the effects of preschool in combination with parental change in well-being. As to this point in the literature, there have been studies on the effects of preschool on low-income children's school readiness and long-term outcomes, along with a discussion about parental income and its effects on these children. However, there is little study on how the two may interact. Prior research just scratches the surface on how changes in income may affect the retention of preschool outcomes, often not directly addressing the issue.

Some of the limited research shows that social policies can affect parental choice in preschool placements. For instance, districts that use vouchers for childcare have been shown to both incentivize lower quality homecare while simultaneously taking away money from the wider system. The money taken out of the system by vouchers could go towards higher quality center-based programs. For example, poor parents who work nights have little choice but to choose homecare for preschool childcare. Some researchers suggest that instead of using vouchers, more funding for preschool centers could address this dilemma by allowing the centers to have fuller and more flexible hours (Fuller, Kagan, Loeb, & Chang, 2004). Other studies have shown that parents in low-income situations may choose higher quality preschool/childcare programs if they have a better economic situation. Indeed, parents who were given subsidies for preschool have chosen more quality placements (Shlay, Tran, Weinraub, & Harmon, 2005; Weinraub, Shlay, Harmon, & Tran, 2005).

Also a family's economic health has been shown to affect the amount of time children stay in preschool. Childcare costs are a concern for poor families and putting a child into kindergarten may save families money. But delaying kindergarten for a year, especially for at-risk children, significantly increase their test scores upon entry and their growth in the first few years of grade school (Datar, 2006).

Puma (2010) reports on some long-term effects of Head Start as students enter grade school using a representative data set of Head Start programs around the nation. Many of the subgroups in the study had favorable impacts fade by first grade. However, there were a few exceptions. For instance, a subgroup of children whose parents had no depressive symptoms, which can be directly influenced by income, sustained the benefits of Head Start in both the social-emotional and cognitive domains. On the other hand, children whose parents had moderate depressive symptoms showed sustained negative impacts from Head Start in the social-emotional, cognitive, and health domains. This illustrates the potential an income increase may have if it is able to affect factors such as family depression.

The above research, although limited, illustrates that the variables surrounding socio-economic status of families can be viewed as a causal risk factors and not a simple marker or variable factor as some posit. This means that the conditions of poverty can be viewed as changeable and influential to child outcomes. Moreover, they may be some of the more important factors policy makers in education should consider if the goal is to improve school and life outcomes for low-income, at-risk children. As affirmed by Karoly et al. (2005), current preschool intervention programs do not fully close the gaps between the disadvantaged and their middle class counterparts. On the other side of the same token, Morris et al. (2005) argues that income increase alone is not the most effective way of dealing with poor children's risk in school. Programming and policies that mediate low economic status in conjunction with center-based preschool programming should be able to help slim the gap over the long run.

Summary

Preschool intervention programs help to introduce school knowledge poor children do not get through transmission in the home. This is needed to keep-up with their middle class counterparts. The instruction and surrounding services within effective center-based preschool programs are able to slim the cognitive and social-emotional gaps between poor and middle class children as they enter school. The above research has shown that preschool has the ability to significantly improve school readiness and life outcomes for the poorest children in our country. However, many of the preschool cognitive gains fade out over the course of k-12 education due to the lack of supports.

When income is increased significantly and in the long-term, poor families have extra resources to support and enrich education (both physically and psychologically) when the preschool support system is gone and children move into k-12 schooling. The thought is that these extra-supports and enriched environments should help to slow or stop students from regressing or falling victim to fade out. This, in turn, decreases the achievement gap long-term. All of this is supported in the combined lens of Risk Factor, cultural capital/ social reproduction, and ecological theories.

My upcoming study thus is designed to examine if long-term increases in family income in early childhood for children in low-income households affects the fade out of skills and behaviors gained in preschool. Research on the link between the two may highlight whether or not it would be worthwhile to simultaneously invest in both these realms during preschool and early elementary school ages.

CHAPTER III

METHODLOGY

In chapter three, my study's methodology is examined. First, I argue as to why a quantitative, multivariate approach is the most appropriate for my upcoming research. Then, my study is detailed including research questions, study design, and limitations.

Rationale for a Quantitative, Multivariate Approach.

The objective for my study is to help inform policy makers and administrators on how best to invest resources to better educational outcomes for low-income students. A better understanding of how preschool and family income play a role in school outcomes may allow these decision makers opportunities to focus their efforts to combat the fade out of preschool skills in low-income students. Over the past decade, this constituent has pushed for scientifically based research, and more specifically, quantitative methods. With the enactment of No Child Left Behind in 2001, the United States Department of Education (USDOE) called for scientifically based research to be at the forefront of educational decision making in the country. During a panel conference in early 2002, the USDOE along with major independent educational research organizations defined scientifically based research as a hierarchical model with large, experimental, random assignment or quasi-experimental designs that control as many variables as possible. The research leaders at the conference cited a few key reasons why these methods are desirable. One reason was that these studies push for generalizability, an important factor when trying to set policy on a large scale. Second, they felt these methods create more rigorous and less biased research (Feuer & Towne, 2002). With this definition of scientifically based research, the USDOE set an agenda where large scale, quantitative data would drive policy, which continues a decade later. Therefore, creating a quantitative model that accesses a large representative data set is paramount for my objective of reaching these stakeholders.

Review of past methods.

In addition to the importance of quantitative methods in influencing decision makers, these methods are in line with past explorations into the topics of preschool and income. For the past few decades, researchers have used quantitative measures to examine the extent in which preschool programs affect school readiness, k-12 performance, and life outcomes for at-risk children. A few major examples already mentioned in previous chapters are the research conducted on the Perry Preschool Program by Belfield et al. (2006), as well as the studies such as Joo's (2010), who used large national data sets to create quasi-experimental studies on preschool efficacy. During a similar time frame, influential income/employment researchers such as Brooks-Gunn et al. (2002), Yeung et al. (2002), and Raver et al. (2007) examined the connection between income and achievement in school also using quantitative models and large data sets. Often, in both areas, quantitative analyses were built from the foundation of previous studies (as discussed in Chapter II). Therefore, to investigate to what extent, if any, changes in family income have on the long-term effectiveness of preschool programs, it would be logical to create a quantitative study that incorporates aspects of the previous preschool and income models.

Nature of multivariate analysis.

It is of particular importance for my chosen method to be not only large scale and quantitative, but also have the ability to account for the numerous factors involved in school outcomes for children. For this purpose, multiple regression analysis fits well. As I have previously posited using Bronfenbrenner's ecological theory along with Bourdieu's capital theory, there are many direct and indirect factors that affect children's school and life outcomes. This groundwork paves the way for me to examine the effects of a direct intervention such as preschool in combination with a factor such as family income, which is more removed from the child's immediate level. However, this lens also means that the method I choose must attempt to account for other direct and indirect factors that could influence a child's schooling. Multivariate research seems to be the most logical method to achieve this goal.

Multiple regression analysis seeks to account for all independent variables included in a model and predict if and to what degree each variable has a unique relationship with an outcome, or dependent variable (Spicer, 2005). In my upcoming study, multiple regression will allow me to control all other known variables within a given data set that have been determined to have an effect on cognitive and social-emotional skills in children. A coefficient will predict how much of a relationship, if any, change of income has on the efficacy of preschool in the long-term success for low-income children in school, above and beyond the effects of the other variables.

Research Design

Purpose and questions.

Based on this practical and theoretical grounding, I built the foundations for a large scale, multivariate, quantitative study. The major questions this study is designed to address are:

What effect, if any, does family income have on the fade out of preschool gains as children move through grade school?

What effect, if any, does an increase in family income early in children's lives have on the fade out of preschool gains as children in low-income families move through grade school?

Rationale for research design.

As discussed in Chapter II, past researchers have usually examined income and preschool effects on school outcomes discretely, while my study seeks to incorporate and connect them. Researchers have examined the effects of increasing family income and have found small but significant correlations between increases in income and improved school outcomes (both social-emotional and cognitive) for low-income children. It is assumed that added family income allows for more educational resources while also allowing for a more enriching educational environment in these low-income households. But an increase in income may mean less if children are already far behind at the beginning of grade school. It can be equated with filling a racecar with gas while others are already on the track and driving. Meanwhile, preschool researchers have connected preschool programs with better school and life outcomes for child of low-income families. However, much of the early educational gains are statistically lost as students from low-income families move through grade school. This fade out is assumed to be due to children's home environments, resources, and school quality. Helping low-income children keep-up with their middle class peers prior to k-12 education without working toward equaling resources between the economic classes so that poor families have the capital to support school growth can be equated to giving low-income children a full tank at the beginning of the race without any prospects of "gassing-up" in the future.

By examining those low-income children who went through center-based preschool and whose families benefited from increased income early in their childhood, the upcoming study may highlight a unique opportunity. The theory is that the gap between poor and middle class children will be slimmed upon entering formal schooling due to preschool intervention, and gaps are less likely to widen as schooling goes forward due to the increase of family resources (both gas at the beginning of the journey and gas stations in the future).

Study's scope.

My study's aim is to examine if there is a connection between an increase in family income for low-income children who have gone through a center-based preschool program and the retention of their gains over those who are of the same status upon starting school and have not experienced an increase in family income. Because of this aim, my study's scope can be narrowed to a few important aspects, while limiting many potential others.

Low-income/ at-risk groups.

The current study is only concerned with those children near or in poverty during early childhood. As stated in many studies from my literature review, the link of both preschool and income increase to improved student achievement is strongest with children in the lowest income groups (Currie & Thomas, 1995; Magnuson & Shager, 2010; Puma, 2010). These are also the groups most vulnerable to fade out (Currie & Thomas, 1995; Lee, 2010; Lee & Loeb, 1995; Ou, 2005). My study then focuses on this group of children, along with other at-risk variations discussed later. Therefore all other groups (i.e. middle income, high income,) are not considered in this study.

Preschool.

Since I am looking at the concept of fade out, I will examine not only low-income children, but also those low-income children who have gone through center-based preschool. For this reason those who have not gone through a center based preschool, even in at-risk groups, are not considered in this study.

Increase in income in early childhood.

Studies have shown that increases in income have small but significant effects on school performance when children are in early childhood and mixed results moving into adolescence (Brooks-Gunn, Han, & Waldfogel, 2002; Gennetian, Castells, & Morris, 2010; Morris, Duncan, & Clark-Kauffman, 2005). Thus, for the purpose of this study only children whose family income changed substantially early in childhood are considered.

Looking for connection.

This study's focus is on the possible *connection* between increase in income and fade out, not necessarily the *nature* of this connection. It is the intention of this study to smell for proverbial "smoke", where if found, subsequent studies can isolated the fire and its sources through a variety of techniques.

Analysis Methods and Procedures

Data and sample.

Using a large data set that is longitudinal in nature is a key component of a study involving the effects of preschool and income change. It allows a researcher to track a group of individuals through multiple years to analyze the effects of a treatment, program, or policy. For this purpose, the Early Childhood Longitudinal Study (ECLS-K) fit the profile.

ECLS-K.

The Early Childhood Longitudinal Study – Kindergarten Cohort (ECLS-K) is a nationally representative survey that includes 21,255 children who were enrolled in kindergarten during the 1998-1999 school year. The study follows students, families, and schools through the cohort's 8th grade year in 2007, making it the first large national data set to follow students from kindergarten through eighth grade. Created by the National Center for Education Statistics (NCES), subjects were chosen using multistage sampling from counties, to schools, to children. The response rate for the school level was 75% and within those participating schools, 92% for children, 91% for teachers, and 89% for parents (Raver, Gershoff, & Aber, 2007).

The ECLS surveys were conducted during the kindergarten, first grade, third grade, fifth grade and eighth grade years (National Center for Education Statistics, 2011). Measures on students, parents, teachers, and administrators, as well as other demographic measures, create a robust data set centered on the children in the study. During the kindergarten year, questionnaires were given in the fall (code=1) and spring (code= 2). Entering first grade, a 30% sample of participants were surveyed (code=3) in the fall and the whole group in the spring (code=4). The full survey was then given in the spring of third grade (code=5), fifth grade (code=6) and eighth grade (code=7) (National Center for Education Statistics, 2011). Since its release, the survey and its measures have been a reliable source for numerous studies (Gershoff, Aber, Raver, & Lennon, 2007; Raver, et al., 2007)

Variables

The variables used in my study rely on three separate but important factors. The first factor for inclusion of a variable is that it is supported in the literature as an important construct connected to a child's cognitive skills or emotional well-being. Those variables that have little to no support from past studies, are controversial, or have not been proven to have an effect on the dependent variables are not included. The second consideration is that the construct is measured in a meaningful way by the ECLS-K. Obviously, if a measure is unavailable in the survey then it is left out of the analysis.

In addition, composites measuring constructs must be deemed to be reliable. Fortunately, a few extensive studies have used the ECLS-K to build and test these variables in order to connected them (or not) to school readiness. I borrow many variables from a key study conducted by Gershoff et al. (2007) who performed factor analyses to build composites for measuring constructs related to cognitive ability and social-emotional competence. Using structural equation modeling analysis, these researchers sought to test whether a construct called "material hardship" could be considered as a separate risk factor from family income when examining children's cognitive and emotional measures. To test this construct, the researchers used the ECLS-K kindergarten year measurements. In creating a complex model meant to show the path in which income and material hardship are mediated to affect cognitive and behavioral outcomes, these researchers created and tested numerous composites not only for their main independent variables, but also for their controls. For the following control variables section, reliability scores for control variable composites are cited directly from Gershoff et al. (2007).

Control variables.

In this study, I include control variables from the ECLS-K, which have been found to affect student achievement both cognitively and behaviorally. The literature from chapter two is often used in justifying the inclusion or exclusion of variables. These control variables include child demographic controls, family controls, and community/school controls collected during the beginning kindergarten year. All controls are used to level the playing field before the main experimental groups are introduced. Since I do not aim to describe how an increase in income may be mediated, keeping the independent variables as background controls is appropriate. This technique has been used by other researchers in examinations of preschool programs and other treatment/posttest studies using longitudinal data (Belfield, Nores, Barnett, & Schweinhart, 2006; Lee & Loeb, 1995). A list of the control variables and specific items on the ELCS used to create these variables are included in Table 1.

***Child demographic controls*.**

The demographic controls include age, race, gender

Age.

Ages on the ECLS-K are reported in months from the fall of 1998, the beginning of the kindergarten year. Age in early schooling is important because, as previously discussed, research has shown a relationship between delaying entry into school and better student outcomes, especially with children in poverty (Datar, 2006).

Race.

Race was also compiled during the first collection in the fall of 1998. From the original race variable on the ECLS-K categories of *Black, Hispanic, Asian, White,* and *Other* were created. Countless studies have illustrated race-based differences in cognitive achievement and social-emotional competence, including many from my above review (Duncan, et al., 2007; Karoly, Kilburn, & Cannon, 2005; Magnuson & Shager, 2010).

Gender.

Gender has been a significant predictor of cognitive and emotional measures (Gennetian, et al., 2010; Joo, 2010; Karoly, et al., 2005). The gender variable was directly adapted from the gender item in the data set collected in the fall of the kindergarten year.

Family level measures.

Family control measures were obtained in the first year of the study, mostly from the parent interviews. These measures include *family education attainment, parental marital status, parental work status, household size, family income, material hardship, parental stress* and *parent investment*. As stated above, many of these are adapted or borrowed from Gershoff et al. (2007). Parenting behavior was purposely excluded from this analysis due to the mixed conclusions surrounding behaviors (such as spanking) and child achievement, especially in a multicultural context (Raver, et al., 2007).

Family education attainment.

Family education attainment was measured in the first year by a single survey item ranging from an 8th grade education or below (1) to doctorate/professional degree

(9). For the purposes of the study, the highest educational level between two parents or the highest education of a single parent is used. The importance of this variable is illustrated by studies that have linked parental education attainment and student performance (Duncan & Magnuson, 2005; Roth, Brooks-Gunn, Murray, & Foster, 1998).

Marital Status.

From the *marital status variable* on the first year survey, parents were put in three groups: married, not married, and unknown. This brakes the original ECLS groups of married (=1) to 1, various forms of single (= 2-5) to 0, and unknown (= 7,-7,-8,-9) to -9. This variable is of importance due to the research linking lower levels of cognitive and behavioral performance with students in single parent households (Duncan & Magnuson, 2005).

Parental work status.

The original categories for the *parental work status variable* on the ECLS were used which included *not in the labor force, looking for work, part time, and full time*. Work status has been shown to be a key factor to include in analyses that examine income due to other benefits (potential gain in other types of capital) and costs (less time at home) that come with employment (Gennetian, et al., 2010; Morris, Bloom, Kemple, & Hendra, 2003).

Household Size.

The number of adults and children in a household was recorded in the fall of the kindergarten year. The *household size variable* is a continuous measure taken directly from this item on the ECLS-K. Household size has been shown to be a partial predictor of both cognitive performance and emotional well-being in school and is usually included in studies of both income and preschool (Gennetian, et al., 2010; Joo, 2010; Karoly, et al., 2005).

Material hardship.

Material hardship is a construct built from the data set including *food insecurity, residential instability, inadequacy of medical care,* and *months of financial troubles*. Material hardship is an important construct to include with income when studying cognitive and social/emotional development (Gershoff, et al., 2007; Raver, Gershoff, & Aber, 2007).

Food insecurity.

Food insecurity (α= .89) is measured by using a created composite within the ECLS-K data. It was created from a series of questions given to parents about hunger or the threat of hunger in the household. The categorical measure is used which included the categories of *secure, food insecure no hunger, and food insecure with hunger*.

Residential instability.

The *residential instability variable* is a single item on the ECLS-K. It asked families how many times they moved since the child's birth which ranged from 0 to 19 (higher numbers indicating residential instability).

Financial troubles.

The *financial troubles variable* is an item in the data set that asked parents if they had serious money problems since their child had been born. The responses were yes or no.

Inadequacy of medical care.

The *inadequacy of medical care composite*, combines the medical insurance coverage item (covered=0, not covered=1), the primary care visit in the past year item (visit=0, no visit=1), and the dental care in the last year item (visit=0, no visit=1) from the ECLS. These three were recoded to covered/visited (=1) and not covered or visited (=4). Adding the three variables and calculating the mean, the range of inadequacy of medical care was 1-4 (the higher the more inadequate).

Parental stress.

Parental stress is a construct that includes two composite variables: parenting stress and depressive symptoms. As discussed earlier, parental stress levels have been shown to have consequences to a child's cognitive and behavioral performance in school, especially in early childhood (Chase-Lansdale & Pittman, 2002; Morris, et al., 2005; Yeung, Linver, & Brooks-Gunn, 2002).

Parenting stress.

The *Parenting stress variable* (α= .66) is a composite built from six items (Table 1) asked to parents. Each ranged from 1(completely true) to 4(not at all true). The higher the score is, the higher the stress.

The *Depressive symptoms* composite (α= .84) was built from 12 items (Table 1) on the data set, all using the CES-D depressive symptoms scale (Radloff, 1977). This scale ranged from 1 (never) to 4 (most of the time). Again, high scores related to high levels of depressive symptoms.

Parent investment.

The parent investment construct includes the variables *purchase of cognitively stimulating materials, parent/child activities outside the home, extracurricular activities,* and *parent involvement in school*. As with parental stress, an enriching environment, or lack thereof, has been link to cognitive and behavioral scores, deserving special attention during early childhood (Duncan, et al., 2007; Magnuson & Shager, 2010; Duncan & Magnuson, 2005).

Purchase of cognitively stimulating materials.

The purchase of *cognitively stimulating materials composite* (α=.64) was created by using three items on the survey: the number of children's book purchased, the number of children's records purchased and if there was a computer in the household for child use. The number of books was recoded into four categories based on the median (1=0-24, 2=25-49, 3=50-99, 4=100-200). The number of records or compact discs was also rescaled from a continuous variable (1=0-3, 2=4-9, 3=10-24, 4=25-100). Having a home computer was rescaled so that no (=1) and yes (=4) kept the same scale as the other items. The average of the three items created a composite scale of 1-4, with higher scores having higher levels of purchasing stimulating material.

The parent/child activities outside the home variable (α=.46) was created by using five items from the ECLS-K data set borrowed from the HOME Scale (Caldwell & Bradley, 1984). All were yes (=1) and no (=0) questions, creating a scale from 0-5 with high number signifying more activities.

Extracurricular activities.

This is a composite (α=.56) of nine items. Parents responded yes or no to these items, which asked whether their child participated in particular extracurricular activities. These scores were summed with the higher the score, the higher the participation in extracurricular activities.

Parent involvement in school.

The parent involvement in school variable (α=.58) was again adapted from eight items based on the HOME Scale. Parents answered yes (=1) or no (=0) (recoded from 1= yes, 2=no) to being involved in activities that are based in a child's school.

Community/ school level measures.

Home location.

For the community, the location of the home variable is a control. This consists of three grouping off of one item in the data set: Urban (large to mid-sized city), Suburban (suburb or large town), and Rural (small town or rural area). Inclusion of this variable is in line with research that links the differing level of neighborhood stress in these environments and children's social and cognitive measurements (Duncan, et al., 2007; Massey, 1998).

School type.

For a school control, the school type variable will be used. This is an item on the survey that broke schools into public and a few private/ parochial school types. For the purpose this study, the variable was recoded to public (=1) and all types of private/religious schools (=0). Often, the distinctions between public and private schools are the higher levels of resources, along with the other types of capital (social, cultural), available at private schools that are often not present in public school. This difference could help predict achievement.

Table 1

Control Variables and ECLS-K Codes

Child Demographic Controls	
Variable Label	**ECLS-K Code**
Gender	GENDER
Race	RACE
Age	R2KAGE

Community/School Controls	
Variable Label	**ECLS-K Code**
Location type	KURBAN_R Made into City and rural
School Type	S2KSCTYP

Family Level Controls	
Variable Label	**ECLS-K Code**
Family Education Attainment	WKPARED
Marital status	P2CURMAR
Parental Work Status	P1HMEMP &P1HDEMP
Household size	P2HTOTAL
Financial Problems:	P1TIMEFI
Residential Instability	P1NUMPLA
Medical Care Composite:	
Medical Insurance	P2COVER
Primary Care	P2DOCTER
Dental Care	P2DENTIS
Food Insecurity	P1FINANC

Family Level Controls Continued...			
Variable Label	**ECLS-K Code**	**Variable Label**	**ECLS-K Code**
Parenting Stress Composite:		*Parent/Child Activities Composite:*	
Harder Than Expected	P2BEPARN	Go to Library	P2LIBRAR
Child Annoys	P2CHDOES	Go to Concert	P2CONCRT
Sacrifice Too Much	P2MEETND	Go to Museum	P2MUSEUM
Feel Trapped	P2FLTRAP	Go to Zoo	P2ZOO
Often Feel Angry	P2FEELAN	Go to Sport	P2SPORT
Hard Child	P2CHHARD	*Extracurricular Activities Composite:*	
More Work than Pleasure	P2MOREWK	Dance Lessons	P2DANCE
Stimulating Materials Composite:		Athletic Events	P2ATHLET
# children's books	P1CHLBOO	Organized Clubs	P2CLUB
# children's records	P1CHLAUD	Music Lessons	P2MUSIC
computer	P2HOMECM	Drama Classes	P2DRAMA
Depressive Symptoms Composite		Arts Classes	P2ARTCRF
Unusually Bothered	P2BOTHER	Organized Performing Arts	P2ORGANZ
Poor Appetite	P2APPETI	Craft Classes	P2CRAFTS
Can't Shake Blues	P2BLUE	Foreign Language Classes	P2NOENGL
Trouble Focusing	P2KPMIND	*Parent Involvement in School Composite:*	
Feel Depressed	P2DEPRES	Fundraises	P2FUNDRS
Everything's an Effort	P2EFFORT	Attended School Event	P2ATTENS
Feel Fearful	P2FEARFL	Parent Teacher Conference	P2PARGRP
Sleep Restless	P2RESTLS	Parent Advisory Group	P2PARADV
Talk Less Than Usual	P2TALKLS	Attended PTA	P2ATTENP
Feel Lonely	P2LONELY	Open House	P2ATTENB
Feel Sad	P2SAD	Contacted School	P2PARINT
Can't Get Going	P2NOTGO	School Volunteer	P2VOLUNT

Main independent variables.

The two main independent variables in the study are center-based preschool status and family income. These two variables were manipulated to create an income/preschool status variable that includes the four study groups.

Preschool status.

For center-based preschool status, the original item on the ECLS-K (P1PRIMPK) was recoded from 8 categories to three: 1 = center based preschool, 0 = no center-based preschool, -9 = undetermined. The two categories used to create the center-based preschool group were the original center-based group (=5) and the head start group (=6). The no center-based preschool group consists of the original homecare arrangements (= 0-4), and the undetermined group is those originally coded as having multiple setting for childcare (=7) or varied setting (=8).

Family income.

As thoroughly discussed in this paper, income has many direct and mediated effects on cognitive performance and social-emotional competence of children (Gennetian, et al., 2010; Magnuson & Shager, 2010; Yeung, et al., 2002). For the family income variable, I used the reported income brackets. Those earning $40,000 or under a year were placed in categories of 5,000 dollar increments (8 in total). Those from $40,000 to $200,000 were placed in differing dollar increments (4 in total). The last category included those earning more than $200,000.

Manipulating these two independent variables, four groups were created: Low-income Constant- No Preschool Baseline group (LCNPB), Middle Income Constant

Baseline group (MICB), Low-income Constant – Preschool group (LCP) and Low-income Increase – Preschool group (LIP).

Low Income Constant – No Preschool Baseline (LCNPB).

This group was created to act as a low baseline group. These are children whose families are in the low-income brackets, under \$20,000 of family income per year. Although the ECLS-K includes incomes up to \$40,000 per year as low-income, as discussed above, the research on income increase in education shows the biggest effects on the poorest children (Dearing, McCartney, & Taylor, 2001; Gennetian, et al., 2010). The family income for this group stayed in the same bracket; meaning they stayed in a \$5,000 range through all the years. These students also did not attend a center-based preschool. This at-risk group form a hypothesized low baseline group, as they did not received any preschool supports and did not benefited from an increase of income during the study.

To create this group, I started with the preschool variable created above (1=preschool, 0= no preschool). Filtering out those who went to preschool, I used the family income reported in kindergarten and set the parameters within that income bracket through the eighth grade year. Altogether, these students represent a group that did not attend preschool and whose family income stayed consistently low through the years.

Middle Income Constant Baseline Group (MICB).

These children come from families with incomes of \$40,000 to \$200,000 a year. Although past research (Dahl & Lochner, 2008; Gennetian, et al., 2010) states that increases in income have little to no effect in middle to higher income families, this group is held constant in the same way as the low constant group. Mimicking the income brackets on the original data set, these children's families are within 20,000 earning (+ or-) from their reported kindergarten income in all follow-up measures through 8th grade, so long as they did not dip below $40,000 in family income. This group is predicted to be the high baseline group.

Low Income Constant – Preschool Group (LCP)

This group includes children who went to a center-based preschool and whose family income began below $20,000 dollars and stayed constantly low. To create this group, I used the beginning income from kindergarten and the preschool status variable. First, I filtered out those who did not go to a center based preschool. Then follow-up income measures through eighth grade were set within the same income bracket as the kindergarten income measure, creating a group whose income stayed within a $5,000 dollar radius and who attended a center -preschool. This is the first of the two comparison groups and will be used as the control group in the upcoming research design.

Low Income Increase- Preschool Group (LIP).

These children, who went to a center-based preschool, have a family income of less than $20,000 during the kindergarten measurement, and their family income increased by at least $5000 from kindergarten to first grade. I did this by setting the first grade income measure to at least two income brackets above the kindergarten measure. This insures that the increase was at least 5,000 dollars, as moving up only one income bracket could signify a much smaller increase (e.g. $9,999 to $10,001 would move a family up one income bracket). This increase was made constant by setting the subsequent years (3rd – 8th grade measures) greater than or equal to this first grade income measure. The group was capped at an increase of 4 income brackets (under a $20,000 gain) to discourage outliers who may have earned a tremendous gain in income. This created a group that has gone through preschool and had an early and sustained increase in income. They are the treatment group in the study.

Altogether, these four groups make the income/preschool status variable.

Table 2

Study Groups

Group Name	**Group Description**
Low Income Constant – No Preschool Baseline (LCNPB):	• Reference/Baseline Group • Kindergarten Family Income Under $20,000 • Family Income within 5,000 dollars through 8th grade • Did not go to a center-based preschool
Middle Income Constant Group (MICB):	• Reference/Baseline Group • Kindergarten Family Income above $40,000 and below $200,000 • Stayed within $20,000 through 8th grade
Low Income Constant – Preschool Group (LCP):	• Control Comparison Group • Kindergarten Family Income under $20,000 • Family income within 5,000 dollars through 8th grade • Attended a center-based preschool
Low Income Increase- Preschool Group (LIP):	• Experimental Comparison Group • Kindergarten family income under $20,000 • Family income increases between $5,000-$20,000 between kindergarten and first grade measures • Family income stays above this level through 8th grade

Why 20,000 in income as a benchmark?

According to the U.S. Department of Health and Human Services, the poverty guideline for a family of five in 1999 was $19,520 (U.S. Department of Health and Human Services, 1999). The U.S. Census Bureau, who uses what they call the Poverty Threshold, put their weighted average measure at $20,127 in 1999. Thus, $20,000 serves as a benchmark for poverty.

Often, low-income studies are conducted using double the government poverty line (Anyon, 2005; Gennetian, et al., 2010; Lee & Loeb, 1995), which would include those in all in the lower income categories (0- $40,000) in the ECLS. This is because many families in brackets immediately above the poverty line still experience hardships due to a lack of resources. However, since studies have shown that increases in family income have the greatest affect on lower income children's achievement (Gennetian, et al., 2010), it seems as though staying at the poverty line is the most appropriate dividing line in the study (Note that the middle income group's starting point begins at $40,000). An option, which is discussed later, would be to include those up to 40,000 as a low/moderate income group in follow-up analyses.

Why $5,000 dollars as increase benchmark?

Aside from the fact that the ECLS-K data set places low-income families within $5,000 increments, there are a few reasons why my upcoming study uses the over/under $5,000 benchmark separating the increase in income group and the constant low-income groups. First, allowing the LCNPB and LCP groups to fluctuate within $4999 will permit a reasonable amount of income flexibility as well as income increases due to inflation. From 1999 – 2007 (kindergarten- 8th grade years) the estimated combined inflation in the

United States was around 24%. With this statistic, those families on the high end of the low-income groups, around $20,000, will have inflation adjusted salaries of just under $25,000, or just below the benchmark of 5,000 dollars. Earnings of more than that could be considered above and beyond inflation adjusted income and may signify a growth in income.

Secondly, as other researchers have described, income increases of $1,000 dollars have shown significant but small improvements in school performance (Morris & Gennetian, 2003). Starting the study examining a growth of $5,000 dollars within a year for our treatment group would hopefully magnify these effects. As with the poverty line, possible follow-up analyses could manipulate the amount of gain the treatment group is allowed, testing for lower and higher increases.

Why only increases from kindergarten to first grade?

As discussed in detail in chapter two, income interventions have been shown to be most effective early in a child's life, due mainly to the extent a young child is nested in the family (Brooks-Gunn, et al., 2002; Gennetian, et al., 2010; Morris, et al., 2005). Ideally, income measures would have been collected since birth. Unfortunately, a limitation of the ECLS-K is that it only starts collecting this data at the onset of kindergarten. Therefore, the first available time to note changes in income is from kindergarten to first grade. Again, possible follow-up analyses could manipulate the time at which the increase in income occurs to tests its affect on social and cognitive development.

Dependent variables.

Cognitive skills.

Cognitive skills are the main dependent variables in the study, as educational measures are the main focus of fade out studies. Cognitive skills are reported by using the Item Test Theory (IRT) scores on the ECLS-K for math (α= .95) and reading (α= .94) (Rock, 2002). The IRT are scaled scores including items and measures from the Peabody Individual Achievement Test Revised (Markwardt, 1997), the Peabody Picture Vocabulary Test-3 (Dunn, 1997), the Primary Test of Cognitive Skills (Lochner, 1990), and the Woodcock – Johnson Psycho- Educational Battery-Revised (Woodcock, 1990). These tests were administered in the spring of kindergarten and subsequent follow-up years. The kindergarten cognitive measures are considered pretests in my upcoming research design with the other administrations as posttests for comparison.

Social-emotional competence.

Social-emotional competence is a second set of measures that are dependent variables in the study. Although not the main focus of the study, behavior in school often affects learning. Because of this, it is of interest to see if there are differences between the study groups, testing if preschool and an increase of income have an effect on perceived behaviors of children. Social competence is measured by borrowing items used by Gershoff et al. (2007) during their structural equation modeling analysis. The composites used in these researchers' study included an average of parent and teacher ratings on children's problem behaviors. However, because the survey only used parent level measures for the first year, they could not be used in my design. In addition, the reliability scores for the teacher items are much higher than parent measures, so they seem to be better measures of the constructs. As with cognitive tests, kindergarten social competence measures are considered pre-tests in the discussion on research design below.

The four variables measuring social competence are the *interpersonal behavior variable,* the *self regulation composite,* the *internalizing problem behaviors variable,* and the *externalizing problem behaviors variable*. All scores are based on teachers' responses on the Social Skills Rating Scale (SRS) (Gresham, 1990) adapted by the ECLS. The reliability statistics are from the psychometric report for the ECLS–K (Gershoff, et al., 2007; Rock, 2002).

Interpersonal behavior (α= .89) was created by using the teacher scores from the SRS. The questions on the SRS asked about levels of behavior that would be considered socially desirable such as helping peers or making friends. The scale ranged from never (1) to always (4) with higher averages signifying high levels of social competence.

The self regulation composite uses two teacher measures from the SRS, self control (α=.80) and approaches to learning (α=.89), to create an average measure ranging from 1-4 with higher numbers indicating higher levels of self regulation. These items asked teachers about children's ability to control themselves and their motivation to learn.

The *internalizing problem behaviors variable (α=.78)* was created by using the teacher reported internalizing behavior score on the SRS. The questions centered on internal depressive characteristics such as low self-esteem and anxiety. The scale (1-4) makes higher averages equate to high levels of internalizing problem behaviors.

Finally, *externalizing problem behaviors variable (α=.90)* uses the teacher externalizing problem behavior scale. This asked teachers a variety of questions surrounding students' outward problem behaviors in school such as arguments and fights.

Table 3

Dependent Variables

Cognitive Skills: Dependent Measures	**Social- Emotional Competence: Dependent Measures**
IRT Math Score	Interpersonal Behavior Variable
IRT Reading Score	Self Regulation Composite
	Internalizing Problem Behaviors Variable
	Externalizing Problem Behaviors Variable

Comparative Analysis/ Analytic Strategy

Cohort study.

This study compares the Low Income Constant –Preschool group (LCP) and Low Income Increase- Preschool group (LIP) in a longitudinal cohort study. These two groups of low-income kindergarteners (cohort 1998) have attended a center-based preschool and only differ in that one group had an increase in family income from kindergarten to first grade which was sustained through eighth grade, while the other group's family income stayed consistently low. Using the starting control variables throughout the study will allow me to set equal aspects of the child, family, and community found in the ECLS-K survey that have been shown to affect school performance, both socially and academically.

To judge performance over time and to explore the concept of fade out, the Middle Income Group (MICB) and Low Income Constant- No Preschool (LCNPB) groups will be used as baselines. With the control variables and these groups, an analysis will be conducted in which the two comparison groups are compared to the baseline groups for differences in performance, cognitively and socially, at four different times through eighth grade.

Ex post facto/quasi-experimental design.

The design of my study is quasi-experimental in nature using ex post facto data. Ex post facto is not a control random experiment; rather, it is a natural experiment created by circumstance. Therefore, the independent variable used as the treatment is not manipulated by the researcher (Ary, Razavieh, & Jacobs, 2002; Murnane & Willett, 2011). The control group in this study is the LCP group, while the experimental group receiving the treatment is the LIP group. The treatment in the study is the increase in income between the kindergarten and first grade. This increase is maintained through the follow-up measures. The design that follows is what Shadish, Campbell and Cook (2002) describe as an untreated control group design with dependent pretest and posttest samples:

Figure 2

Untreated Control Group Design

LIP	NR	O_1	x	O_2	O_3	O_4	O_5
	----------	----------	----------	----------	----------	----------	----------
LCP	NR	O_1		O_2	O_3	O_4	O_5

NR- nonrandom.

The NR in the model means that the two groups are nonrandom. Although random selection techniques were used to create the ECLS data set, the groups that I have created were not made through random selection. Individuals naturally fell into groups based on circumstance. The use of descriptive statistics assists in positing whether or not the groups seem representative of the population.

O- observations.

As you can see in the design, there are two groups: one above and one below the dotted line. The group above the line is the experimental group (LIP). The group below the line is the control group (LCP). The Os are the observations and the underscored numbers are the order they were made in, chronologically. The observations in this study are the dependent tests given in kindergarten/control (O_1), first grade (O_2), third grade (O_3), fifth grade (O_4), and eighth grade (O_5).

X – treatment.

As illustrated in the design, the treatment in the study is only applied to the treatment group (LIP). The treatment, as discussed above, is the increase in income families of the children in this group have experienced somewhere between the observations in kindergarten and first grade.

Putting it all together, the first observation (O_1) serves as a pretest, as no treatment has been experience prior to the testing. Each successive observation becomes a posttest, comparing the control and experimental groups. To examine the construct of fade out, I then layer in the baseline groups of MICB and LCNPB to create Figure 3.

To review, the concept of fade out usually refers to the gaining of school readiness skills by at-risk students, usually through intensive center-based preschool programming. These cognitive and behavioral gains show a slimming of the gap between these at-risk students and their middle class counterparts upon entering k-12 education (Duncan, et al., 2007; Lee, 2010; Lee & Loeb, 1995). But as these at-risk students move through grade school, their school performance regresses back to that of those at-risk students who did not get this intensive preschool and away from their middle class peers. These children's gains literally "fade out".

Adding the MICB group as a top baseline and the LCNPB group as a bottom baseline will allow me to study the trajectory of the two comparisons groups' performances as they regress from the MICB group and near their LCNPB peers. Thus, I can compare the different levels of fade out between the two comparison groups through the years.

Figure 3

Untreated Control Group Design with High and Low Baseline Groups

MICB Group baseline O_1__________O_2_________O_3__________O_4__________O_5

LIP	NR	O_1	x	O_2	O_3	O_4	O_5
	--						
LCP	NR	O_1		O_2	O_3	O_4	O_5

LCNPB Group baseline O_1_________O_2__________O_3__________O_4__________O_5

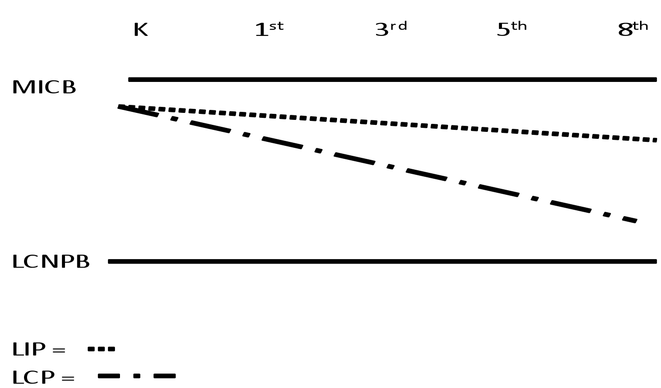
Hypothesis and Null Hypothesis

The research/alternative hypothesis.

The LIP group's mean cognitive and social/emotional scores will not regress away from the MICB group's mean scores and towards the LCNPB as much as the LCP group's scores due to the added support of an increase of income during early childhood.

Figure 4

Research Hypothesis



Null hypotheses.

There is no relationship between increase in income early in childhood for low-income children who have gone through center-based preschool and grade school cognitive skills.

There is no relationship between increase in income early in childhood for low-income children who have gone through center-based preschool and social competence scores.

Preparing the Data

As with any quantitative study using a large data set, care needs to be taken so that errors in imputing or creating variables do not end up affecting the final analysis. Before any analysis starts, the data needs to be "cleaned". This means that possible errors when converting the raw data from the items on the ECLS-K data set for analysis need to be corrected. Exporting that data to a statistical packaging program will allow me to systematically clean the data and run a descriptive analysis prior to my regressions.

SPSS

As practiced by most quantitative researchers, I will be using a statistical package for my descriptive statistics and regression analyses. The program I have chosen is the well-known and widely used Statistical Package for the Social Sciences or SPSS. SPSS is a program originally created in the 1960's for the statistical analysis for social science research. Today, managed by IBM, it is one of the most used statistical packages in all of research.

Descriptive statistics

Descriptive statistics enable a researcher to organize, describe, and summarize a study, providing the context and adding meaning to the study's results (Ary, et al., 2002). They also help to illustrate the variables and groups throughout the study, working hand in hand with inferential statistics.

One of the main roles of descriptive statistics is to check if the variables in a study are desirable before inferential techniques are employed. What is assumed desirable depends on the type of analysis that will be run which, in the case of my study, will be multiple linear regression analysis.

With multiple linear regression analysis, a few assumptions are made about the variables included in the study. First, it is assumed that the distribution of each continuous independent variable is a normal bell curve. If a variable is not at an interval or ratio level, it must be dichotomous or dummy coded. Second, the independent variables should have a linear relationship to the dependent variable(s). Third, the independent variables should not be highly correlated with one another. And, fourth, there should be enough cases to run a significant regression (Murnane & Willett, 2011; Spicer, 2005).

To check that these assumptions are met, descriptive analyses will be used before and during the regression. The number of cases, mean, standard deviation, range, and histograms will be the main descriptive statistics of use at the beginning of the analysis. These measures will allow me to check for normality and indentify possible problems as I move towards my regressions. For example, small numbers in my groups could mean that I have a lot of missing data that I would need to account for. Or, an abnormally high standard deviation for a group could call into question the normality of the distribution. Values outside of the expected response range may signify that the data has not been adequately cleaned. Histograms can visually show the range of each variable and if it adheres to the normal bell curve. A more detail description of some of the major problems that may be faced during the running of descriptive statistic and the regression are discussed below.

Issues of concern before and during regression analysis.

It may not be realistic to account for or fix all problems, as all analyses are imperfect to some degree. However, acknowledging, prioritizing, and accounting for possible data issues will make for a stronger more accurate analysis:

***Missing data*.**

Missing data in the sample can be a major issue. The extent of the problem depends on the amount and the nature of the data missing. Since a regression will exclude missing cases, care needs to be taken to make sure that those missing are not substantially different from the included cases. Running descriptive statistics comparing those in the missing category and those included can give a clue as to how different the missing group is from the group included. If they appear to be substantially different, using a systematic method to fill-in the missing data may be necessary. Beyond the nature of those missing and those included, if too many cases are missing, there may not be enough data to run the regression. Again, a systematic method to put values to the missing cases would be a necessity.

Because the ECLS-K data have some variables already documented in other studies to be missing a substantial amount of cases, I will most likely have to assign value to some missing data. In order to maximize the amount of children in the study and in accordance with others who have used this data set, maximum likelihood estimation or another imputation model most likely will be applied (Gershoff, et al., 2007; Raver, et al., 2007). These methods use the observed values of all the variables in a data set to estimate and fill-in missing values. Imputation methods are available on a number of data analysis software programs, including SPSS.

Skewness and kurtosis.

Skewness is how symmetrical the data is. An extremely high or low skew would mean that the median and mean are far from each other. Kurtosis is how peaked the "bell curve" is in a distribution of a variable. Both of these issues speak to the normality of the distribution in a variable. If skew or kurtosis scores are above 3 or below -3 then they are considered abnormal (Shadish, Campbell, & Cook, 2002). SPSS calculates these scores for each variable. If a variable has a high skew or kurtosis, then it may need to be transformed. Whether or not to transform a non-normal variable and the type of transformation would depend on the specifics of the variable and the context.

Linearity.

The main analysis in the study will be a multiple linear regression so it is important that each independent variable has a linear relationship with the dependent (Shadish, et al., 2002; Spicer, 2005). Because the main independent variables in my study are dummy coded groups, any relationship between the groups and the reference group will be linear in nature (Ary, et al., 2002; Spicer, 2005). Still, I will check my other control independent variables for linearity. This is important because problems within the control variables could play a role in how the groups interact with the dependent measures. For instance, if a variable's relationship with the dependent is not linear but curvilinear, the correlation between that independent and the dependent may be underestimated. This could possibly cause an overestimation for being included in a study group (Shadish, et al., 2002; Spicer, 2005).

The main way to test for linearity is to examine scatter plots or residual statistics between the independent variables and the dependent variables during the analysis.

Again, how I will handle a lack of linearity between an independent variable and dependent variable will largely depend on the situation and the importance of the variable.

Multicollinearity.

Multicollinearity takes place when two or more independent variables are highly correlated. This is a problem in a regression because one's correlation to a dependent will mask another's. To help avoid this, I can run a correlation matrix with all independent variables before the regression. If two variables are highly related a few things may be done. First, I can check if the variables are input correctly. If there is no error in creating the variables an option could be to delete one or the other because their high correlation ultimately means they are most likely measuring the same thing.

In general, problems with missing data, skew, kurtosis, linearity, and multicollinearity, along with the other issues, weaken a regression but do not necessarily invalidate it. Since I am not as concerned by any single independent variable as I am my dummy coded groups, these problems are less of an issue. As always, context, importance, and priority will ultimately determine how I handle these situations as they arise.

Assuming the data is clean, the distributions of variables are normal, the independent variables are linear in relation to the dependent, and the independent variables are not too highly correlated with one another, I can report the characteristics of my main groups in a table and then begin my regression analysis.

Regression Model

As discussed above, multivariate analysis is the most appropriate approach to this research study. To isolate the treatment effect of increase in income, multiple regression analysis will be run. Because all dependent measures (IRT test scores and social-emotional competence scales) are continuous, Multiple Linear Regression model (MLR) will be conducted using ordinary least of squares analysis (OLS). Layered over this model will be contrast group coding design with dummy variables. All together this will make a Least Squares Dummy Variable Regression (Davis, 2010).

General multiple linear regression model.

$$\mathbf{y = b_0 + b_1 x_{i,1} + b_2 x_{i,2} + \ldots + b_k x_{i,k} + e}$$

y= cognitive test score/ social-emotional score

b_0= y- intercept/constant

$x_{i,k}$= value of k^{th} independent

b_k= coefficient of k^{th} independent

e= error term/noise variables

Above is a basic multiple linear regression model. All independent variables values ($x_{i,j}$) with their coefficients (b_k), the constant (a), and error/noise (e) are added together in order to create parameters and predict the dependent/outcome variable. When all data is added to the equation, each individual independent variable's contribution to the prediction of the dependent variable, holding all other independents in the formula constant, can be calculated. In other words, how much each independent variable can be used to predict the dependent variable uniquely, above and beyond the affects of any other variable included in the regression. The b_i/ coefficient lets us know the amount and direction in which the variable affects the dependent. This coefficient, along with an acceptable significance level (p-value), and the strength of the correlation based on the measure of variability between the independent and dependents (r and r^2 - both discussed later) is what can allow a researcher to correlate an independent variable with a dependent variable in a regression (Ary, et al., 2002; Shadish, et al., 2002).

OLS process description.

Layered with the general multiple regression model is ordinary least square (OLS) analysis. OLS analysis will allow me to fit regression lines with the least amount of combine vertical variance amongst all data in the distribution, or smallest sum of squares. It does this by using all the data points in the set to find the intercept (a) and slope (b) that will most limit the sum of squares or variance in the data. These lines are the "best fit" for the population regarding the particular independent and the dependent variables (Shadish, et al., 2002; Spicer, 2005).

Dummy variables/ contrast coding.

Layered on top of the general linear OLS design will be complex dummy contrast group coding design (Davis, 2010; Shadish, et al., 2002). A dummy variable uses the values of 0 and 1 to indicate the absence or presence of a categorical effect that is thought to affect the outcome variable (dependent). Within a regression, dummies are often called binary variables. To use dummies, categories must be mutually exclusive, meaning one cannot be part of more than one category in the variable. All categorical controls will be dummied in order to be added to the regressions.

In my upcoming study, along with the categorical control variables, the reference and comparative groups within the preschool/income status variable will be used in dummy form. This means that when inputting these groups into the regression, each group will create a new variable with the group being examined given a value of 1 and all other groups given a value of 0. Because I am using more than two groups, this is considered complex dummy contrast group coding (Davis, 2010).

When using OLS regression in combination with dummy contrast coding, it is important to avoid what is commonly known as the “dummy variable trap”. The dummy variable trap has to do with the concept of multicollinearity, or when two or more independent variables are highly or perfectly correlated. If all dummy values are added, their sum would equal 1 which would be identical to the coefficient of the constant. This would erroneously make it appear that there is a one- to-one (or-1) relationship between the independents and the dependent (Davis, 2010; Shadish, et al., 2002).

To avoid this trap, the middle income constant group (MICB) will be a reference variable and will not be assigned to a dummy variable. This is known as using k-1 contrasts, k being the number of categories (Davis, 2010; Spicer, 2005). This will leave three dummy variables created for the other groups: LCNPB (d_1), LCP (d_2), and LIP (d_3). The coefficients of these dummy variables will be compared to the coefficient of the middle income constant group. In other words, these groups’ beta scores will be a comparison from their mean scores to the middle income group’s mean score instead of all in the study.

The use of middle income as the reference group gains support from the prior discussions of fade out. The concept of fade out is usually examined by comparing an at-risk group against their middle class peers. Thus, making this group the reference group within the regression is a near perfect link between the statistical analysis and the conceptual design.

All together this regression design is known as least squares dummy variable regression (Davis, 2010). The simplified regression model in my study is below follows.

Dependent (IRT score or emotional competence score) = $d_1 + d_2 + d_3$ + Control variables + ε

Main regressions.

Separate regressions will be run for each of the variables within the dependent constructs using the same beginning controls. Again we are examining the concept of fade out through a natural experiment and thus only want to make sure everything is set equal before the treatment (increase in income). This will leave five regressions for each dependent variable to be tested, one pretest and four posttest measures for comparison.

Table 4

Main Regressions

Pretest: Kindergarten	**Posttest #1: 1st Grade**	**Posttest #2: 3rd Grade**	**Posttest #3: 5th Grade**	**Posttest #4: 8th Grade**
IRT Math (O_1)	IRT Math (O_2)	IRT Math (O_3)	IRT Math (O_4)	IRT Math (O_5)
IRT English (O_1)	IRT English (O_2)	IRT English (O_3)	IRT English (O_4)	IRT English (O_5)
Social Competence (O_1)	Social Competence (O_2)	Social Competence (O_3)	Social Competence (O_4)	
Self Regulation Composite (O_1)	Self Regulation Composite (O_2)	Self Regulation Composite (O_3)	Self Regulation Composite: (O_4)	
Internalizing Problem Behaviors (O_1)	Internalizing Problem Behaviors (O_2)	Internalizing Problem Behaviors (O_3)	Internalizing Problem Behaviors (O_4)	
Externalizing Problem Behaviors (O_1)	Externalizing Problem Behaviors (O_2)	Externalizing Problem Behaviors (O_3)	Externalizing Problem Behaviors (O_4)	

Secondary tests.

Using the same variables, design, and regression model, secondary tests of interest will also be attempted, crossing other at-risk groups into the two comparison groups. Testing for differences between these groups will not only create a more robust study, but will also identify more specific groups in which increase in income appears to play a lesser or bigger role. Potential groups have been place in Table 5 below. Although these cross groups would add to the analysis, the ability to use them is dependent on the amount of cases available.

Table 5

Possible Secondary Groups for Study

Low Income /Race	**Low Income /Gender**	**Low Income /Types**
Black	Male	Desperately Low ($0-9,999)
Hispanic	Female	Low ($10,000-19,999)
White		Moderately Low ($20,000-39,999)

Important Terms for Regression.

Analysis of variance/significance.

The significance level, also known as the confidence level or the p-value, defends against Type I error, or the chance that a researcher will erroneously rejected the null hypothesis (Ary, et al., 2002; Spicer, 2005). This significance level is preset by the researcher and usually follows industry norms. In social sciences, the significance level of .05 is the usual norm with special note going to any relationship with a level less than

.01. A p-value of .05 means that the researcher is willing to give a 5 % chance that the null hypothesis is rejected by chance alone (Ary, et al., 2002). F-tests, for overall fit, and t-tests, for individual variables, are used to check for significance and give p-values when a regression is run.

F-test.

Running an F- Test is important to check for normality and fitness of data in a linear regression. F-tests in a multiple regression divide the between group variance by the within group variance to get an F-ratio. This basically explains if and to what extent the variance within the study can be explained outside of the normal variance (error variation) within the variables. The higher the F-value, the more the variance is due to between group differences and the easier to reject the null hypothesis. Consulting a f-ratio chart will allow for rejection or acceptance of the null hypothesis based on the given ratio, the degrees of freedom and the selected significance level (Ary, et al., 2002; Shadish, et al., 2002).

T-test for independent samples in main independent groups.

The main t-tests in this study will be examining if group means are statistically and significantly different. Mainly, this is the difference between the means of the LIP, LIP, and LCNPB groups and the mean of the MICB group accounting for the standard error difference between the groups, or the expected difference if the null hypothesis were true (Ary, et al., 2002; Shadish, et al., 2002). If calculating by hand, you must calculate the degrees of freedom and consult a t-value statistical table to see if the t-value is large enough, based on the selected significance level and degrees of freedom, to reject the null hypothesis.

Although both the f-tests and t-tests can be computed by hand, most researchers use packaged data analysis programs to do so. Using SPSS, t-test and f-test scores will be automatically part of the results of my regression analyses.

Comparing means/ regression coefficients b and b*.

The unstandardized/unit regression coefficient (b) compares the mean of the independent to the mean of the dependent, allowing a researcher to describe how much and in what direction an independent variable is related to a dependent variable. A negative b means a negative relationship. A positive b means that as the independent increases, so does the dependent. With a continuous independent variable, b describes how much the dependent would change for every additional unit of the independent. However, with dummy coded variables (my main groups) b will represent how much the dependent variable changes by being a member of each group (Davis, 2010; Shadish, et al., 2002).

The only difference between b and beta (b*) is that b* is standardized, measures standard deviations, and b describes the relationship in actual units. The advantage of using b* is that when looking at multiple variables, it will give a standardized score for comparison (Ary, et al., 2002; Spicer, 2005). For example, weight and height may be used to predict football ability. But since one pound and one inch are not the same units, it would be inappropriate to use b to compare the effects each had on football ability. Instead you would use the standardized measure b*. Since our main comparison groups are examining cognitive or emotional scores across different years, b* would be more appropriate. Again, the regression coefficients (b and b*) will be automatically calculated by SPSS.

Correlation coefficients: r&r^2.

Correlation coefficients are used to describe the strength of the correlation between variables. They analyze the standard scores of the reference group and independent variables creating a score from +1 (a perfectly positive correlation) to -1 (a perfect negative correlation), with 0 being no correlation. The closer the correlation coefficient is towards either of the poles (-1, +1), the stronger the correlation (Ary, et al., 2002; Spicer, 2005).

To obtain the correlation coefficient, the Pearson product momentum coefficient, or the Pearson r score, will be used. In addition to being the most widely used method of gaining a correlation coefficient, the Pearson r score assumes that the relationship between variables is linear, which matches the assumption in my regression model. The r - score will describe the strength of a correlation. The r^2 score, also known as the coefficient of determination, will give the degree to which one variable can be used to predict the other. It is a measure of the percentage of variance in one variable that is associated with the variance in the other (Ary, et al., 2002; Spicer, 2005). In the case of a regression model, r^2 will describe the amount of variance within the dependent variable that is explained by all of the independent variables in the model. In other words, it is how well the whole model predicts the dependent variable. Although there is no standard percentage that would be considered a strong r^2 as this also depends on the model, it is quite rare that a regression model can predict more than 40% of the variance in a dependent variable in social science research. As with f-test, t-test, and beta scores, the r and r^2 will be reported by SPSS in the regression analysis.

Rejecting the Null Hypothesis and Accepting the Alternative Hypothesis.

Rejecting the null.

In order to reject the null hypothesis in each regression the p-value for the f-test and the t-tests need to be analyzed. Again, the fit of the whole regression needs to be statistically significant as well as the relationship between the MICB and the LCNPB, LCP, and LIP groups. For this, the p-values must meet the .05 level.

Accepting alternative hypothesis.

In order to accept my experimental hypothesis, in addition to first rejecting the null hypothesis, the regression coefficient (b*) for the experimental group needs to have a higher value (in this study, most likely less negative) that the regression coefficient for the control group for some of the follow-up years, relative to their starting positions in kindergarten. Thus, to find the total amount of fade out in each group I will take the group's beta for each particular year and subtract it from the pretest/kindergarten beta to create a fade out value (FO). The higher the total FO is, the larger the amount of fade out. So, in essence, to accept my hypothesis for any of the dependent tests, the LIP group must have a smaller FO value than the LCP group every follow-up (O_2 though O_5) for a particular dependent. The formula for calculating FO is included below:

$$\mathbf{FO} = \mathbf{b_{1x}} - \mathbf{b_{xy}}$$

$\mathbf{b_{1x}}$ = Starting beta from kindergarten pretest (O_1) for x group

$\mathbf{b_{xy}}$ = beta of group x for y follow-up observation (O_2 through O_5)

FO = Total amount of fade out

After the discussion of significance and fade out through the regression coefficients, the correlation coefficients (r and r^2) can be layered into the discussion to give more contexts to the analysis. These measures can help describe the strength of the relationships but can only be applied if the null hypothesis is first rejected.

Threats to Validity

Threats to internal validity.

As Creswell (2009) states internal validity threats are "experimental procedures, treatments, or experiences of the participants that threaten the researcher's ability to draw correct inferences from the data about the population in an experiment" (p. 162). Because the design has a pretest, posttest, comparison groups, and is a cohort of similar aged children, many threats to internal validity are minimized in my study. There are a few threats, however, that must be considered.

History.

One of the biggest threats to the internal validity of the study is history. Threats due to history usually involve outside events during the experiment that can influence the outcome beyond the treatment (Creswell, 2009; Shadish, et al., 2002). Changes may occur from kindergarten to eighth grade that have nothing to do with an increase in income to influence cognitive and social-emotional performance. However, the main concern in my study is the prior history outside the scope of the data set that may have influence on the results. For example, the financial history of children's families before kindergarten is unknown in the study. So there could have been families who were at higher income levels and for some reason (childcare obligations, loss of job, etc.) family income fell shortly before kindergarten. Then, right after kindergarten, income increased back to a normal level for that family. This type of validity threat could cause type I error were I am accepting increase in income as a predictor of less fade out, where growing up mostly in a higher income bracket before kindergarten may be the predictor for this case. In an inverse situation, increase in income for a low- income family that came right before kindergarten, type II error could be at threat.

My study's main way of limiting these threats to validity is the use of robust control variables in a regression. In these cases, many differences in child, family, and community measures will most likely be evident as compared to families who are truly of the financial level. Still, this threat to validity is a weakness of my study and the ECLS-K data set as a whole.

Selection Bias.

A second threat to internal validity in my study may be selection bias. Selection bias occurs when participants who are selected for a group have certain characteristics that predisposed them to have certain outcomes (Creswell, 2009). The groups in my study are natural control and experimental groups, and were not randomly selected. Because the groups are nonequivalent, it must be an assumption that there is some selection bias present. For example, parents that have more drive or are brighter may be the ones that are able to secure a better job and increase their income. Children may inherit these characteristics and perform better. This would mean that those in the treatment group would be predisposed to perform better and grow faster than those in the control group.

Given that this threat to validity must be considered, there are many checks that limit this risk. The fact that there are two comparison groups and that pre and post tests are given weakens this threat to validity (Shadish, et al., 2002). Major differences in the pretests of these two groups should be noticed if a high level of selection bias is present.

Threats to construct validity.

Threats to construct validity usually center on whether what is being measured matches the concept that is targeted to be measured (Creswell, 2009; Shadish, et al., 2002). As stated above, the main independents of cognitive ability and social-emotional competence are based on well-established tests in the fields of cognitive science and psychology.

My main construct in the study is fade out. As discussed above, using the baselines of Middle Income Constant and Low Income constant is in line with the research and definitions given for fade out. Past researchers, as I do, often test fade out by comparing those at-risk children who went through preschool programs to both their middle class and low-income/at-risk peers who did not go to center-based preschool.

Threats to external validity.

External validity deals with the ability to extrapolate the results of a study to the population being studied (Creswell, 2009; Shadish, et al., 2002). Although the ECLS-K is a nationally representative survey, the groups used in the study may or may not be reflective of this. The use of descriptive statistics and the potential use of weights will determine to what extent the study can be generalized to all populations. This leads to a discussion of priorities as it applies to validity.

As Shadish et al. (2002) posits, different studies prioritize different types of validity. This is mainly due to practical reasons. The type of validity valued is usually based on the type of study and its end goal(s). For my study, internal and construct validity are prioritized over external validity because I am examining a problem in a new way. Before definitive links to populations and tests such as structural equation modeling can take place to look at the nature of a relationship, first there needs to be evidence that there is a relationship between those at-risk children that go through center-based preschool and whose families experience an increase in income and the fade out of preschool skills. If there is no smoke, there is no need to see the source of the fire or for whom it directly affects.

Limitations

Data set.

The ECLS-K provides a data set advantageous to my study. To start, it has a survey item on early childhood educational experience as well as measures on student performance and family income every year from kindergarten to eighth grade. Additionally, it measures these variables in multiple follow-ups using the same tools. However, one major weakness of the survey is that it does not go back into family income before kindergarten. As discussed in the validity section, this may add to type I and type II error threats. Another weakness is that the data set does not speak to the quality of preschool children are receiving, which could also have a lasting effect (Durlak, 2003; Karoly, et al., 2005). In addition, much of the information, including the income variable, is parent reported. This introduces the possibly of more bias and error that cannot be controlled for within the current study.

Multiple regression.

A general limitation of multiple regression analysis is lack of causality. As discussed above, multiple regression is used to predict a relationship and the strength of connection between a dependent variable and multiple independent variables. All results from the analysis are correlations, meaning this method can describe a connection between variables but cannot definitively conclude a causal relationship. The nature of a significant relationship predicted in a regression needs to be view through the context in order to explain or hypothesize the possible "why". And again, this study's main aim is to discover whether or not a relationship exists. If so, it will be up to future explorations to further explain the nature of the relationship(s).

CHAPTER IV

ANALYSIS

With the study outlined and limitations discussed, the study analysis was completed. This includes a discussion of the descriptive analyses, regression analyses, and results.

Descriptive Analysis of Independent Variables:

Before running the study's multiple regression analyses, descriptive analyses were conducted to test and prepare the independent variables. As outlined in Chapter III, this involved exporting and cleaning the data, checking values, ranges, and standard deviations, analyzing the kurtosis and skewness, and analyzing missing values.

Exporting and cleaning.

Each independent variable, for use individually or within a composite, was exported from the ECLS-K public use file to SPSS. Once in SPSS, all variables were cleaned, transformed, and necessary composites were formed as specified in Chapter III. Composites were made by first transforming each item into the appropriate scale (1-4) using the recode command in SPSS, and then using the compute command to combine several variables into one by taking the mean of all included scores.

The major study groups were also created by using the compute command and manipulating the preschool and income variables. Once each individual group was created, they were then combined into one variable (*all groups*). Finally, the *all groups* variable was dummied, creating LCNPB, LCP, and LIP variables, with MICB as the comparison group.

Once all individual, composite, and dummy variables were cleaned and created, descriptive analyses were run. As discussed in Chapter III, descriptive statistics need to confirm the normality of the independent variables that are to be included in the linear regressions before the analyses can take place. Although a few of the independent variables had to be transformed, due to the results of preliminary descriptive testing, most adhered to the principles of normality. The results of these descriptive analyses, including histograms for any continuous variable, can be made available upon request.

Values, ranges, and standard deviations.

First, the values and range of values were analyzed. Nearly all variables adhered to normal value ranges. All categorical data, including dummied variables, reported only values for the categories included. Within continuous variables, typical ranges and standard deviations were noted for all except the *stimulating materials composite,* which had a high standard deviation. Analyzing the histogram, the variable was bimodal. This meant that families either had very low levels of simulating materials in the home or very high levels of materials, with few in the middle of the continuum. Because of this, the decision was made to create a dichotomous variable out of the composite. The cut-off point between low levels and high levels of simulating materials was the mean 2.7, which is close to the theoretical mid-point of 2.5. Those below 2.7 in the composite variable were included in the low levels of materials group and those 2.7 or above were included in the high levels of materials group. For the purpose of including the variable in the regression, it was then dummied for high levels of stimulating materials.

Kurtosis and skewness.

As with the analysis of the values, nearly all scores for kurtosis and skew were within the accepted normal range of -3 to 3 (Shadish, Campbell, & Cook, 2002). Although a couple of scores were outside of this range, only one seemed serious enough to deem it necessary to transform. Kurtosis was a bit high for depressive symptoms and medical care composites. However, looking at the histograms, these variables had bell curves with slightly steep peeks. Because of this, the decision was made to leave them as they were.

The one variable that had an abnormally high kurtosis was residential instability. The original kurtosis score of 17 was way outside the normal range of -3 to 3. Analyzing the histogram, the high peak of the bell curve was due to the fact that the large majority of respondents only lived in one or two places by the kindergarten year. Because of this clustering around the low levels of the variable, it was transformed into a dichotomous variable. Using the median (2) and mean (2.18), those that lived in more than two places were categorized as having high levels of residential instability with those at two or below having low levels of residential instability. For inclusion into the regression, the variable was dummied for high levels of residential instability.

With normality examined and appropriate measures taken for those independent variables that violated the norm, Table 6 illustrates the mean and standard deviation of all the control variables as related to the study groups.

Table 6

Descriptive Statistics of Independent Control Variables for Study Groups

Groups: Mean Number SD	**MICB**	**LNPCB**	**LCP**	**LIP**	**Combined/ Total**
Age (months)	74.76 5469 4.37	74.57 325 4.61	74.81 267 4.42	74.34 194 4.39	74.74 6255 4.39
Household Size	4.47 5542 1.07	4.75 333 1.66	4.63 271 2.05	4.66 198 1.61	4.49 6344 1.19
Family Education Attainment	5.99 5542 1.72	2.85 333 1.34	3.07 271 1.17	3.44 198 1.26	5.62 6344 1.93
Parenting Stress Composite	3.44 5525 .418	3.24 326 .577	3.27 266 .505	3.34 195 .542	3.42 6312 .439
Extracurricular Activities Composite	1.59 5540 .484	1.17 333 .307	1.24 270 .359	1.24 198 .381	1.54 6341 .486
Parent Involvement Composite	2.80 5540 .606	2.04 333 .682	2.05 271 .724	2.18 198 .732	2.71 6342 .665
Medical Care Composite	1.16 5540 .394	1.44 333 .649	1.37 271 .670	1.42 198 .677	1.19 6342 .446
Parent/Child Activities Composite	2.43 5542 .766	1.93 332 .800	1.93 270 .840	1.92 198 .776	2.37 6342 .789
Depressive Symptoms Composite	1.36 5521 .354	1.67 326 .570	1.70 266 .563	1.66 195 .624	1.40 6308 .403
Categorical Dummy Variables: Proportions					
Black	.045	.295	.387	.298	.081
White	.790	.241	.287	.355	.725
Hispanic	.084	.364	.207	.242	.109
Asian	.046	.010	.030	.035	.044
Other Race	.035	.090	.089	.070	.041
Female	.493	.465	.542	.490	.493
Parents Married	.931	.330	.284	.348	.854
Public School	.648	.970	.967	.944	.688
Urban Setting	.338	.505	.539	.455	.359
Rural Setting	.189	.252	.244	.232	.196
Stimulating Materials High	.745	.129	.118	.197	.669
Residential Instability High	.203	.360	.335	.413	.225
Full-time Work	.977	.565	.604	.723	.927
Part-time Work	.018	.163	.122	.128	.034
Food Insecure- No Hunger	.015	.243	.226	.121	.040
Food Insecure- Hunger	.002	.063	.081	.051	.010
Financial Trouble	.102	.390	.385	.398	.141

What is clear from these statistics is that the three low-income group, and especially the LCP and LIP experimental groups, are very similar went it comes to these background variable. This was to be expected as the experimental groups were built to come from similar background. This contrasts the middle class baseline group whose measures on many variables differed significantly.

Analyzing missing values.

After examining the distribution of the data and its normality, the focus turned to the number of valid cases each variable had for inclusion into the regressions. Analyzing the descriptive statistics, the missing data ranged from a low of 0.1 % to a high of 16.3%. The variables with the highest valid percentage were demographic measure and the composite variables. On the contrary, family specific measure seemed to have higher levels of missing data. This is not surprising considering the more intimate information needed to create such variables make those such as food insecurity, marriage status, and educational background harder to collect. Because some variables had a relatively high percentage of missing cases, a decision had to be made about whether to ignore or use methods to replace these data points. With the specific nature of the study groups, the missingness of the data, and the modern expectations of rigorous research, the decision was made to use methods to impute missing values.

Study Groups:

With the size of the study groups (LCP and LIP) relatively small, preservation of cases in the data became important. As stated previously, the more cases an investigator inputs into a regression, the higher the chance of finding significant relationships between variables and the stronger the regressions will be overall. With missing measures, the two study groups numbered between 200 and 300 cases each depending on the dependent measure. Since the data used in the regressions are from multiple collections over multiple years, the number of valid cases would decrease due to some natural attrition (people leaving the study for one reason or another). This would eventually bring the number of subjects in each group in 8th grade to be about half of what they started with in kindergarten. Attrition cannot be controlled in an ex post facto study, but preserving as many subjects as possible at the beginning of the study is within the researcher's hands. Thus, this became a major factor when deciding what methods to use to deal with missing data.

Missingness of data.

The missingness of data refers to the reason why subjects/cases in a survey have missing or incomplete data. The three main types of missingness are Missing Completely at Random (MCAR), Missing at Random (MAR), and Not Missing at Random (NMAR). MCAR means that the mechanism for the data to be missing is not related to the dependent variable or any other independent variable within the study. These missing values are observed to be missing by chance alone. MAR, on the other hand, is a little misleading as titled. MAR means that the mechanism in which the data is missing is not related to the dependent variable in the study, but may be related to another independent variable in the study. NMAR takes place when the missingness of a variable is related to the dependent variable (Scheffer, 2002). The methods for dealing with missing data should depend mainly on the type of missing data one has in the study.

Methods for handling missing data.

The two main methods used to deal with missing data are ad hoc and imputation. Ad hoc methods include ways in which a researcher ignores the missing data and should only be used if data is MCAR (Graham, Cumsille, & Elek-Fisk, 2003). Some of the most popular ad hoc methods include listwise deletion, pairwise deletion, and mean substitution. Mean substitution is simply replacing a missing value with the mean of all observed cases for that variable. This method will introduce a high level of bias if the missing data is not MCAR because it is highly possible that the missing values do not center near the mean of those observe. Listwise deletion throws out a whole case (individual) if there are any missing data points for that case. This method will cause bias if the data is not MCAR and also will remove a lot of subjects from study even if there are relatively low levels of missing values. Pairwise deletion ignores only the missing parts of a data set, preserving the actual amount of cases. If a person does not answer an item on a survey, pairwise deletion ignores only that data point but leaves that person and the rest of her or his data in the study. While preserving the amount of cases in a study, pairwise deletion introduces as much bias as listwise deletion if the data in not MCAR. Also, since each independent variable will have a different number of valid cases, it is very difficult to use pairwise in a regression. Since much of the analysis and statistics associated with a regression are based on the sample size, pairwise deletion would make the regression difficult if not impossible to interpret.

The other main methods of dealing with missing data are imputation including single imputation, such as Estimation Maximization (EM), and Multiple Imputation (MI). Single imputation methods are statistical analyses in which all observed data points within a data set are used to replace missing values with predicted values. While better than using ad hoc methods especially when dealing with a substantial amount of missing data, it is still not ideal. Because each missing value is replace by just one predicted value, variance within the missing values is not accounted for by these methods. Therefore, single imputation methods are still best used when data are MCAR.

Similar to single imputation, multiple imputation (MI) builds statistical models by using observed data to create predicted values for missing data. However, unlike single imputation, MI runs numerous simulations with slightly different models, due to the variance in the observed, to get multiple predicted values for each one missing value. These predicted values can be pooled (averaged) to get a new predicted value for each missing value. Since this method attempts to account for uncertainty within the missing data, it is the better method to use if the data is not MCAR (Wayman, 2003).

Current study's method for Missing data.

When creating any analysis, the intersection of rigor and practicality can become polarizing forces. This is certainly true for missing values analysis. The quickest most practical methods are ad hoc and they are used often in educational research. Unfortunately these are often not the best methods for handling missing data and thus, introduce a great deal of bias to the statistical conclusions of many educational research projects, peer reviewed or not (Wayman, 2003). Fortunately, statistical analysis programs such as SPSS are making complex missing values analyses more accessible to those who are not experts in these types of statistics. Because of these programs, the gap between the most rigorous choice and the most practical choice has been slimmed. For this reason, I was able to focus more on the right thing to do in the current context.

Missingness of current data.

To figure out how to handle missing data in the study, I had to analyze how much data was missing and the type of missingness involved. Fortunately, I could check for both using the missing values analysis in SPSS. This gave me the option to compute the overall statistics for the missing values in the data set as well as run the Little's MCAR test. Little's MCAR test analyzes the missing data for significant patterns/relationships between missing variables. If there are significant patterns (i.e. if one variable measure is missing in a case often another variable measure is missing), then Little's MCAR will report this significance ($p \leq .05$) and it can be assumed that the missing data is not MCAR. If no significant relationship between the variables is noted, then it can be assumed that the data is MCAR.

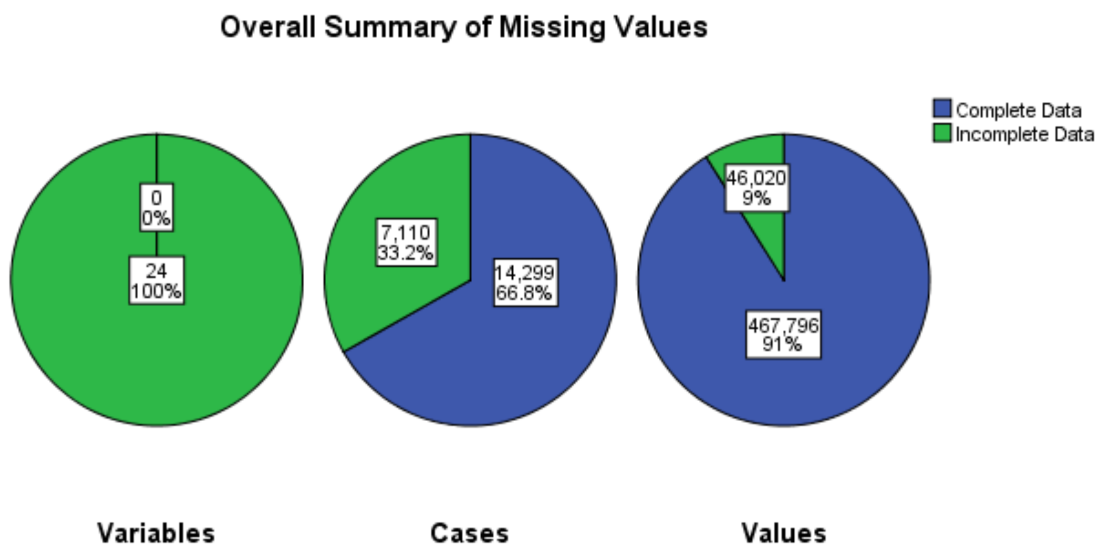
Below are the results of the Missing Values Analysis. Included in this analysis are a Summary of the Missing Values (Figure 5) and the Missing Values Patterns (Figure 6), both created with the Analyze Pattern tab in SPSS. The results of the Little's MCAR test revealed that there were significant relationships between missing variables. Due to this result, the data was assumed to be not MCAR.

As shown in Figure 5, only 9% of the values in the study were missing. However spread across all of the cases, 33.2% were incomplete. Due to the percentage of cases with incomplete data, deletion methods seemed to be the less prudent choices. Looking solely at the Summary of Missing Values, imputation was the most likely choice of methods, but the type of imputation depended on the missingness of the data.

The results of the Little's MCAR test revealed that there were significant relationships between missing variables ($p \leq .001$). Due to this result, the data was assumed to be not MCAR. Analyzing Figure 6, a clear pattern can be observed.

Figure 5

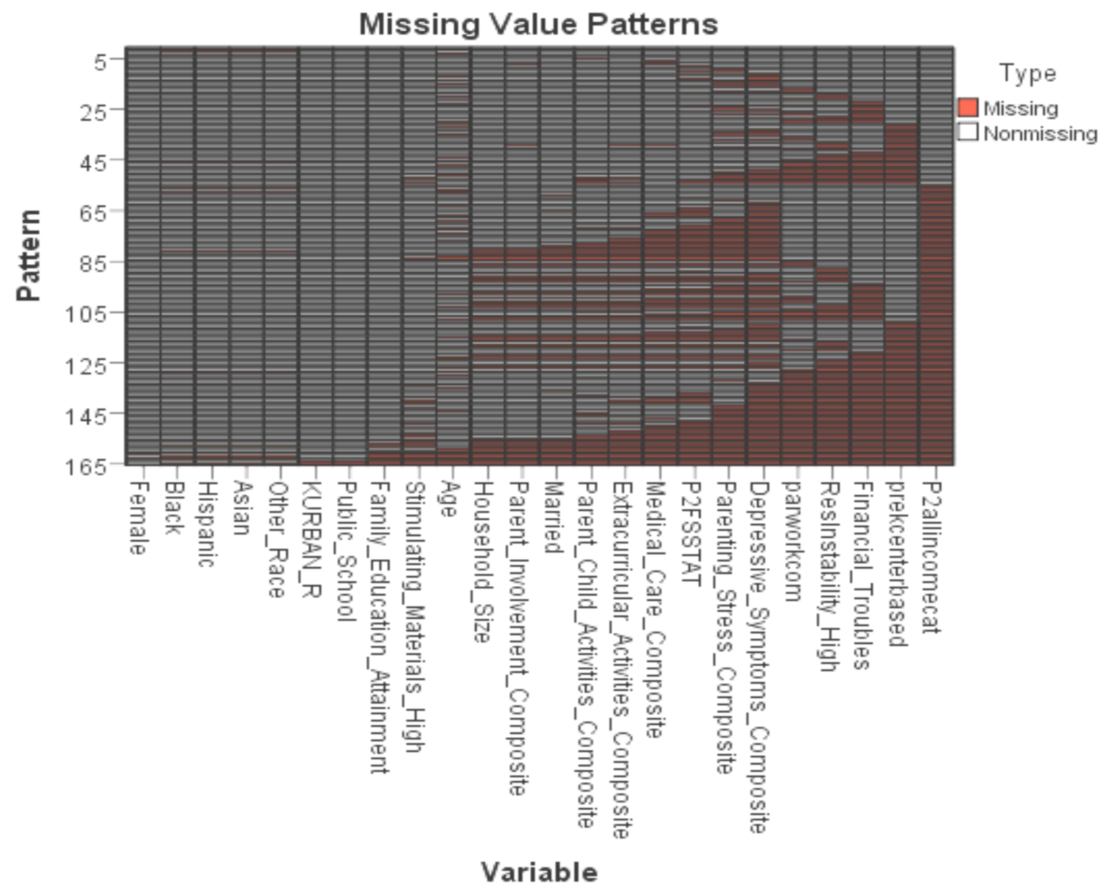
Summary of Missing Values



If the data were MCAR, the Missing Value Patterns chart would have random clusters of missing data points. In this case, clearly there is a pattern looking at the right side of the chart, corroborating the findings of the Little's MCAR test. The data in the study seemed to be MAR, with missing values patterns between specific independent variables. With the findings from the overall missing values summary and the missingness patterns present, multiple imputation was the clear option for dealing with missing data in the current study.

Figure 6

Missing Values Patterns



Multiple imputation for missing values.

Before running the MI analysis, it was important to make conjectures as to what patterns were present. The greatest patterns observed in Figure 6 started with the income data missing, followed by some of the more sensitive measures such as financial troubles, work status, and depressive symptoms. As stated prior, some of the more personal measures are more difficult to collect for obvious reasons, especially for those that are at an extreme or downtrodden position in society. For these reasons, I hypothesized that those missing were more likely to be lower income and have measures viewed as less desirable for the more sensitive variables.

Using SPSS, a new data file was created using multiple imputation. All independent variables, both continuous and descriptive, were added to the multiple imputation under the Analyze tab in SPSS. The default of five imputations was used and automatic was selected under the Methods tab, which had the program scan the data and identify the correct method for completing the MI. Because of the MAR patterns of the missing values, the program used regression to impute the values. When finished, it created a new file with six active sets of data for each of the variables, the original and the five data sets that included the imputed values. During any future analysis these five imputed data sets could be pooled together to create one measure. These pooled statistics were used when creating the new study groups and during the subsequent regression analyses.

Results of multiple imputation.

The descriptive analysis of the control variables after the MI seemed to fit the hypothesized results. Again, of interest were mainly the income variable and other more intimate family measures. Table 7 illustrates the findings for the key variables within the major missing values patterns. The original, imputed, and pooled means are displayed to show the difference between the original measure and the measures imputed along with the effects on the overall data set. All of the statistics from the MI are available upon request.

Table 7

Means of Original, Imputed, and Pooled Values of Variables in Missing Patterns

Variable	**Original Mean**	**Imputed Mean (average)**	**Pooled Mean**
Income	7.44	6.45	7.24
*Financial Troubles	0.240	0.253	.244
Depressive Symptoms	1.461	1.620	1.482
*Center-based Preschool	0.571	0.568	0.570
*Residential Instability	0.301	0.306	0.302
*Full-time Parental Work	0.860	0.833	0.854

*Categorical Data- Reported in proportion

Examining Table 7, the original income mean and the mean of the imputed values was nearly a whole income bracket, or 5,000 dollars less. This adjusted the overall mean by .2 of an income bracket. *Financial troubles, depressive symptoms,* and *residential instability* were all higher in the imputed values and *full-time work* and *center-based preschool* were lower. All these fit the predicted conclusion that those of lower income were more likely to have missing values, which then connected to higher scores on less desirable measure and lower scores on more desirable measures.

Confident in the MI and its measures, new dummy variables could be made using the new imputed data for inclusion into the upcoming regressions. This included reconfiguring the four study groups. The new descriptive statistics for these groups in relation to all of the other independent variables are reported in Table 8 below.

The descriptive statistics from the original data from Table 6 and the pooled data in Table 8 are very similar, which is to be expected since the study groups are highly defined. The main difference between the two is that numbers of valid cases within the low-income groups (LCNPB, LCP, and LIP) are larger after imputation.

Table 8

Descriptive Statistics of Independent Control Variables for Study Groups – Multiple Imputation Pooled Values

Groups: **Mean** **SD (averaged)**	**MICB (n=5741)**	**LNPCB (n=451)**	**LCP (n=349)**	**LIP (n=278)**	**Total Sample (n=6819)**
Age (months)	74.779 4.372	74.674 4.632	74.878 4.302	74.436 4.438	74.763 4.450
Household Size	4.47 1.082	4.72 1.696	4.57 1.996	4.59 1.605	4.50 1.220
Family Education Attainment	5.98 1.720	2.86 1.317	3.10 1.184	3.39 1.267	5.52 1.969
Parenting Stress Composite	3.436 .416	3.249 .565	3.270 .513	3.317 .523	3.410 .441
Extracurricular Activities Composite	2.429 .764	1.901 .792	1.919 .821	1.967 .781	2.350 .789
Parent Involvement Composite	2.799 .610	2.036 .659	2.042 .706	2.163 .712	2.684 .698
Medical Care Composite	1.191 .503	1.624 .877	1.450 .773	1.604 .915	1.250 .590
Parent/Child Activities Composite	2.430 .765	1.902 .791	1.919 .829	1.967 .783	2.350 .792
Depressive Symptoms Composite	1.361 .352	1.663 .551	1.679 .542	1.649 .577	1.409 .407
Categorical Variables: Proportions					
Black	.045	.283	.394	.321	.090
White	.788	.243	.265	.325	.706
Hispanic	.084	.360	.214	.228	.115
Asian	.048	.018	.034	.042	.045
Other Race	.035	.096	.093	.084	.044
Female	.492	.458	.520	.480	.490
Parents Married	.930	.323	.275	.347	.833
Public School	.647	.970	.960	.936	.696
Urban Setting	.340	.474	.508	.447	.362
Rural Setting	.188	.259	.247	.220	.197
Stimulating Materials High	.745	.125	.121	.204	.650
Residential Instability High	.205	.364	.341	.400	.231
Full-time Work	.977	.559	.589	.680	.917
Part-time Work	.018	.157	.124	.137	.037
Food Insecure- No Hunger	.015	.234	.216	.128	.045
Food Insecure- Hunger	.002	.061	.072	.056	.012
Financial Trouble	.105	.387	.385	.407	.150

This is advantageous to the upcoming regression analyses because attrition is relatively high and consistent across these three low-income groups. As evident in Table 9 below, each group slowly lost cases, ending with around half of the cases they started with by grade eight. Besides the number of group members, Table 9 shows the mean scores of each group for every cognitive dependent variable (math and reading) in the study. Social competence means for the main study groups are available in Appendix A.

Table 9

Cognitive Dependent Variable Pooled Means and Cases for Main Study Groups

Cognitive Dependents **Mean** **Number**	**MICB**	**LCNPB**	**LCP**	**LIP**	**Total (All Groups)**
Math IRT (O_1)	41.864 n=5071	28.311 n=428	30.187 n=524	31.793 n=265	39.545 n=6288
Math IRT (O_2)	69.272 n=4988	50.469 n=428	51.748 n=526	53.679 n=265	65.826 n=6207
Math IRT (O_3)	110.152 n=4406	79.815 n=328	82.627 n=401	86.391 n=202	105.321 n=5337
Math IRT (O_4)	134.470 n=3591	103.165 n=248	106.141 n=299	109.972 n=143	129.857 n=4381
Math IRT (O_5)	151.306 n=3237	123.674 n=189	124.486 n=226	130.517 n=101	147.741 n=3753
Reading IRT (O_1)	51.382 n=5070	39.044 n=359	40.265 n=489	40.954 n=248	49.3631 n=6165
Reading IRT (O_2)	86.909 n=4987	62.736 n=389	64.924 n=507	66.479 n=258	82.706 n=6140
Reading IRT (O_3)	140.470 n=4403	103.962 n=321	108.438 n=390	110.831 n=201	134.795 n=5315
Reading IRT (O_4)	162.420 n=3592	127.279 n=248	130.367 n=299	135.681 n=143	157.251 n=4282
Reading IRT (O_5)	183.156 n=3228	145.009 n=183	147.328 n=223	153.487 n=100	178.352 n=3734

Regression Analyses.

With the independent variables cleaned, transformed, normality examined, and missing values imputed, the focus could finally be turned to the study's regression analyses. First the proper use of weights had to be examined. Then, social emotional regressions were performed. Finally, the main cognitive regressions, mathematics and reading, were run to test the study's main hypothesis.

Weights.

In statistical models, weights are used to link the sample used in an analysis to the population, protecting again type II error. Often, a study over or under samples different characteristics in a population, especially if the study does not use simple random selection. Using a weight can adjust the relative strength of each observation so that the results can more closely match the population. Along with possible sampling error, the ECLS-K, as with most large-scale surveys, did not use simple random selection to identify study subject. For practical reasons (there is no list of all kindergarteners in the whole United States) the sampling used a complex multistage method. Therefore, the use of a weight that takes into account design effects can help a researcher more accurately generalize to a population outside of the study (Hahs-Vaughn, 2005).

Since all controls and groups were created from the spring kindergarten year survey, I used the weight created by the ELCS for the second student, teacher, and parent collection (spring of kindergarten year). This was then normalized to match the sample size in the data set using the derived mean weight procedure and further adjusted using the average design effects (DEFF) to account for design error (Hahs-Vaughn, 2005).

Normalized.

The weights for the ECLS-K sample are summed to the total of the population. For the analysis, I needed the weight to be normalized so it summed to the sample size. Unlike other statistical programs, SPSS does not automatically do this during the analysis. I had to calculate the normalized weight using the derived mean weight procedure (Hahs-Vaughn, 2005). To do this I divided the raw weight by the mean of the weight, bringing the weighted cases to just over 21,000, nearly identical to the sample size of 21,409 for the whole data set. Using the compute variable tab in SPSS, I transformed the original weight to this normalized weight.

DEFF.

Statistical programs such as SPSS are designed to deal with data from a simple random sample by default when running an analysis. If left untreated, the program will tend to underestimate the standard error if a researcher is using data from a complex sample. To account for the design effects of complex sampling, the normalized weight needed to be further transformed using DEFF.

DEFF is the adjusted standard error from design error. It makes a ratio from the variance found in the actual sampling design and the variance that would be expected if it were a simple random design. To use the DEFF to account for this design variance, I divided the normalized weight by the DEFF as reported by the ECLS-K for the spring of kindergarten year for all students (Tourangeau, Nord, Sorongon, & Najarian, 2009). Calculations and weight results for the normalized and the DEFF normalized weights can be found in Appendix B. Once the DEFF normalized weight was created, the main regression analyses of the study could be conducted.

General outline of all regressions.

As outlined in Chapter III, separate least squares dummy variable multiple regressions were run for each dependent variable. Using SPSS, all appropriate independent variables, including the dummied major study group and the DEFF normalized weight were added into the regression equation. All statistics reported are of the pooled data. If not reported directly by SPSS, the pooled data was created by taking the mean of the five MI data sets.

Descriptive statistics in regressions.

Along with the regression statistics, descriptive statistics, correlation matrices, and residual statistics were all reported. These measures spoke to the normality and proper implementation of the regressions, insuring that all the appropriate variables were included and that multicollinearity between variables was not present. In all regressions, these reported measures were well within the normal range, which allows the discussion of the following sections to focus on the main regression results. The SPSS output files that include the descriptive and correlation statistics are available upon request.

Regression results.

The three main sections reporting inferential statistics in SPSS were the ANOVA, Model Summary, and Coefficient tables. The ANOVA table was first analyzed for the F-value and its significance. As discussed in Chapter III, the F-value measures the significance of the whole regression. If the F-value is measured to be significant, the Model Summary and Coefficient table could then be analyzed for specifics. The Model Summary gave R^2 values. Again, this value gives the relative strength of the whole regression by reporting the proportion of variance within the dependent variable that is explained by the regression. Finally, the Coefficient table reported the significance (t-test) for each individual independent variable and the standardized regression coefficient (b*) for each variable. These measures confirmed which independent variables were predictors of the dependent scores, including to what extent and direction. All continuous variables with interpretable standardized regression coefficients measured change in standard deviations. All dummied variables, such as the main study groups, reported proportional change for being part of that group in relation to the comparison group of that variable (e.g. female vs. male). ANOVA, Model Summary, and Coefficient tables for all regressions are available upon request.

OLS Regressions And Results: Social Competence

The first dependent scores that were examined were the social competence measures. Although the alternative hypothesis could not be accepted in the social competence regressions, analysis and discussion of the finds resulted in some of these measures being included as independent variables within the cognitive regressions that followed.

Internalizing Problem Behaviors.

Internalizing Problem Behaviors is a teacher reported variable created from the teacher survey of the ECLS-K. Centering on internal behaviors such as anxiety and depression, a four-point scale was used to rate children with a higher score signifying a higher level of Internalizing Problem Behaviors. Table 10 gives the results of the four OLS regressions including the F- value, R^2, the significant independent predictors of these behaviors, and the major study groups' correlations.

The results of all four OLS regressions gave significant (p=≤.001) F-values ranging from 10.475 in kindergarten to a low of 4.917 in the fifth grade observation (O_4). The proportion of variance explained (R^2) by the model only range from .042 to .026. Both F and R^2 were fairly low as the models were judge to only explain about 4% of the variance within the dependent variable.

Table 10

MLR Results: Internalizing Problem Behavior

Results of OLS Regressions: Internalizing Problem Behaviors: Independent Predictors Standardized Regression Coefficient (b*)

Independent Variable	**Spring Kindergarten(O_1) n=6405; F=10.475*** **	**Spring 1st Grade (O_2) n=5710; F=9.430*** **	**Spring 3rd Grade (O_3) n=4576 F=8.237*** **	**Spring 5th Grade (O_4) n=4112 F=4.917*** **
Age	-.032**	-.033*	-.035*	
Female	-.027*	-.037**		-.051**
Asian	-.026*	-.031*		-.032*
Hispanic		-.036*		
Black			-.043*	
Married	-.034*	-.046*	-.057**	-.048*
Household Size				.045**
Public School			.033*	
Urban Setting	-.029*			
Rural Setting	-.070***			
Medical Composite	.029*			
Food Insecure - Hunger			.032*	
Parenting Stress	.029*	.044**		.037*
Depressive Symptoms		.039*		.056***
Financial Troubles	.089***	.053***	.043*	
Extracurricular Act.	-.05**		-.036*	
Parent Involvement		-.036*		
Main Study Groups				
LNCPB		.049*		
LCP	.061***	.043*		.055*
LIP			.040*	
Proportion of Variance Explain (R^2)	.040	.040	.042	.026

*p=≤.05; **p=≤.01; ***p=≤.001

Independent control predictors.

Although the predictors were a bit spotty across the years from kindergarten to fifth grade, there were some constant predictors that did emerge. Those independent variables that had more than one regression coefficients (b*) that were significant (p≤ .05) are described as consistent predictors. From the background research on behavior there were no major surprises in terms of the independent predictors.

The child demographic measures of age, gender and race all had significant correlations to Internalized Problem Behaviors. Age had a significant negative regression coefficient for the first three data points in kindergarten, first and third grades (b*= -.032,-.033,-.035). This means that older starting ages of kindergarteners correlated to less Internalized Problem Behaviors. Females also had fairly strong negative betas in three out of the four regressions, meaning that females were less likely to be associated with internalized problem behaviors (b*= -.027,-.037,-.051). Asians were also less likely to be connected with these behaviors as compared to whites (b*= -.026,-.031, -.032).

Family level measures that had multiple years of significant correlation with internalized behaviors were marital status, parenting stress, depressive symptoms, and financial troubles. Being married was negatively correlated to Internalized Problem Behaviors across all regressions (b*=-.034, -.046, -.057, -.048). This means that those children whose parents were married in kindergarten had lower levels of these behaviors, holding all else equal. Parenting stress, depressive symptoms, and financial troubles were, not surprisingly, positively correlated with internalized problem behaviors. Parenting stress was significantly correlated to Internal Problem Behaviors during the kindergarten, first, and fifth grade regressions (b*=.029, .044, .037). Financial troubles during kindergarten held a significantly positive relationship for the first three regressions (b=.089, .053, .043). Finally parent depressive symptoms in kindergarten had a correlation to high levels of Internalized Problem Behaviors in the first grade and fifth grade regressions (b=.039, .056).

Main study groups correlations.

As for the main study groups, the only groups that had more than one measure significantly correlated with Internalizing Problem Behaviors was the LCP group. Three times it had significant betas (.061,.043,.055), but they varied in size with no clear pattern emerging (strengthening or weakening). These betas mean that the LCP had higher levels of reported internalized problem behaviors than the middle class baseline group. Both the LNCPB and LIP groups had only one regression in which they were significantly correlated with higher levels of reported Internalized Problem Behaviors compared to the middle class comparison group.

Externalizing Problem Behaviors.

Like Internalizing Problem Behaviors, Externalizing Problem Behaviors is a measure created by the ECLS-K adapted from the Social Rating Scale (SRS) completed by the primary teacher each collection year up to fifth grade. These items centered on more aggressive behaviors that are judged to be a problem in the classroom. Again, high values signified higher levels of Externalized Problem Behaviors. F-values, R^2, and significant predictors of Externalized Problem Behaviors are included Table 11.

As compared to Internalizing Problem Behaviors, the regressions for Externalizing Problem Behaviors had much stronger F-test and R^2 values. The proportion of variance explained by the models ranged from a high of .136 in third grade to a low or .110 in fifth grade, or 13.6- 11%. Externalizing behaviors also had more constant predictors. Whereas Internalizing Behaviors only had one predictor that had significant betas in all years, Externalizing Problem Behaviors had several.

Independent Control Predictors.

Age, gender, and race all were constant predictors in of Externalizing Problem Behaviors. As with internalizing behaviors, age for kindergarteners was negatively correlated with higher levels of Externalizing Problem Behaviors [b*= (-.039)-(-.046)].

Table 11

MLR Results: Externalizing Problem Behaviors

Results of OLS Regression: Externalizing Problem Behaviors: Independent Predictors Standardized Regression Coefficient (b)				
Independent Variable	**Spring Kindergarten(O_1) n=6405; F=31.306*** **	**Spring 1st Grade (O_2) n=5731; F=32.007*** **	**Spring 3rd Grade (O_3) n=4606 F=26.917*** **	**Spring 5th Grade (O_4) n=4136 F=19.267*** **
Age	-.044***	-.046**	-.039**	
Female	-.226***	-.241***	-.243***	-.246***
Asian	-.031**	-.028*	-.040**	-.042**
Black	.076***	.081***	.075***	.063***
Married	-.066***		-.073***	-.075***
Household Size	-.081***	-.099***	-.067***	
Family Education	-.048**	-.058***	-.076***	-.068***
Public School	-.058***	-.057***		
Urban				.038*
Rural			.035*	
Medical Composite			-.035*	
Parenting Stress	.098***	.087***	.104***	.073***
Depressive Symptoms			.043**	
Residential Instability		.029*		
Extracurricular Act.			.034*	
Parent/ Child Activities	-.034*			
Parent Involvement		-.036*		
Main Study Groups				
LNCPB				
LCP	.051***	.055**	.042*	
LIP			.040*	*.048
Proportion of Variance Explain (R^2)	.117	.132	.136	.110

*p=≤.05; **p=≤.01; ***p=≤.001

Gender was a strong predictor in the study. Girls were correlated to 22.6 to 24.6% lower mean scores on the Externalized Problem Behavior scale as compared to boys. This seemed to grow stronger each measure as the negative coefficients grew larger each successive measure. For race, being Asian was correlated with lower levels of problem behaviors as compared to whites [b*= (-.028) - (-.042)] and being black was significantly linked to higher levels of Externalizing Problem Behaviors as compared to whites (b*=.063 - .081).

As for family measures, being married and having higher family education levels were negatively correlated with Externalized Problem Behaviors in each regression, while parenting stress in kindergarten was a strong positive predictor each year (b*=.073 - .104). Two of the more surprising independent predictors were public school and household size. Attending a public school was a negative predictor for the first two regressions and household size was a negative predictor in the first three regressions.

Main study groups correlations.

Again, the LCP group had three years of significant regression coefficients. The first three years the LCP group was positively correlated with externalized problem behaviors. This meant that when compared to the middle class baseline, the LCP was significantly correlated to higher levels of reported externalizing problem behaviors. The LIP group had significant betas in the 3rd and 5th grade regressions, where as the LNCPB group had no significant difference with the middle income baseline group.

Interpersonal Behaviors.

The Interpersonal Behaviors scale was created, as were all the social-emotional measures, from items on the SRS. These behaviors are those that are considered socially desirable. Higher values (1-4) relate to higher levels of these behaviors. The results of the four regressions for Interpersonal Behaviors are reported in Table 12.

Table 12

MLR Results: Interpersonal Behaviors

Results of OLS Regression: Interpersonal Behaviors: Independent Predictors Standardized Regression Coefficient (b)				
Independent Variable	**Spring Kindergarten (O_1) n=6405; F=27.852*** **	**Spring 1st Grade (O_2) n=5716; F=25.700**	**Spring 3rd Grade (O_3) n=4562; F=20.587*** **	**Spring 5th Grade (O_4) n=4086; F=19.021*** **
Age	.057***	.050***	.036*	
Female	.190***	.211***	.209***	.250***
Asian				.037*
Black	-.057***	-.042**	-.053**	-.040*
Married	.049**	.038*	.076***	.062**
Household Size	.033**	.051***	.036*	
Family Education	.056***	.051**	.051**	.064**
Public School	.051***	.049***		
Urban Setting	.049***			
Rural Setting			-.033*	
Parenting Stress	-.080***			-.052**
Depressive Symptoms				-.037*
Financial Troubles	-.037**			
Residential Instability			-.43*	
Extracurricular Act.	.032*			
Stimulating Materials	.031*	.050*		
Parent/ Child Activities				.046*
Parent Involvement	.046**	.042**		
Main Study Groups				
LNCPB				
LCP		-.057**		
LIP		-.035*		
Proportion of Variance Explain (R^2)	.105	.108	.108	.110

*p=≤.05; **p=≤.01; ***p=≤.001

The Results of the four OLS regressions for Interpersonal Behaviors gave similar F-test and R^2 values as Externalizing Problem Behaviors. The proportion of variance in the Interpersonal Behavior scale explained by the regression models ranged from .105 to .110, or 10.5% to 11%. Many of the same predictors for Externalizing Problem Behaviors held for the Interpersonal Behavior regressions. However, since Interpersonal Behaviors were measuring levels of desirable behaviors, these predictors had the opposite coefficient values (i.e. if positively correlated with Externalized Behaviors, they were negatively correlated with Interpersonal Behaviors and vice versa)

Independent control predictors.

Again, age, gender, and race were constant predictors throughout these regressions. Age was a strong predictor in the first three regressions from kindergarten to third grade, but positive this time (b*= .057, .050, .036). Girls were also strongly and positively correlated with Interpersonal Behaviors. This correlation seemed to get stronger as time went by, starting at a standardized beta of .190 in kindergarten and gradually moving to .250 in fifth grade. Being a black student was a constant predictor, as it was negatively correlated with Interpersonal Behaviors each regression.

For family measures, being married, household size, the level of family education, parent involvement and going to public school were all positive constant predictors of Interpersonal Behaviors. Parenting stress was the lone negative predictor with more than one significant regression coefficient. All in all, these independent predictor variables (although coded opposite) were very similar to the Externalizing Problem Behaviors regressions.

Main study groups correlations.

Each of the main experimental groups had only one significant beta across the four years. The LCP had a beta of -.057 in the first grade regression, while the LIP groups had a beta of -.035 for the same year. Once again, the low baseline group (LNCPB) had no significant difference between its mean score and the middle income baseline group.

Self Regulation Composite.

Table 13

MLR Results: Self Regulation Composite

Results of OLS Regression: Self Regulation Composite: Independent Predictors Standardized Regression Coefficient (b)				
Independent Variable	**Spring Kindergarten (O_1) n=6405; F=43.066*** **	**Spring 1st Grade (O_2) n=5767; F=38.578*** **	**Spring 3rd Grade (O_3) n=4619; F=28.607*** **	**Spring 5th Grade (O_4) n=4174; F=8.302*** **
Age	.111***	.086***	.054***	
Female	.215***	.228***	.233***	.132***
Asian		.027*	.046***	
Black	-.071***	-.072***	-.064***	-.083***
Married	.060***	.051**	.090***	
Household Size	.048**	.052***	.029*	
Family Education	.074***	.080***	.089***	
Public School	.048***	.060***		
Urban Setting	.032*			
Rural Setting	.014*			
Food Insecure - Hunger				-.057***
Parenting Stress	-.090***	-.076***		
Financial Troubles	-.036*			
Residential Instability			-.038*	
Extracurricular Act.	.044**			
Stimulating Materials	.047***	.054***		
Parent/ Child Activities			.046**	.046*
Main Study Groups				
LNCPB		-.046**		
LCP	-.046**	-.064***		
LIP		-.041**		
Proportion of Variance Explain (R^2)	.155	.154	.143	.046

*p=≤.05; **p=≤.01; ***p=≤.001

The final social competence measure to be studied was the Self Regulation Composite. This measure was built from two variables in the ECLS-K data set, Self Control and Approaches to Learning. Higher values (1-4) connect to higher levels of Self Regulation. The results of these four regressions appear in Table 13.

The results of the four OLS regressions yielded higher F-test and R^2 values than all of the other sets of social competence regression, except the fifth grade measures. The proportion of variance explained by the regression models started at 15.5% in kindergarten but fell to 4.6 % in fifth grade. Significant independent predictors closely mirrored those found in the Interpersonal Behaviors regressions.

Independent control predictors.

As with the other social-emotional regressions, age, gender, and race were major predictors of Self Regulation. Age started as a strong positive predictor (b*=.111) and held on to a lesser extent through the third grade regression. Female status was a strong positive predictor of Self Regulation (b*=.215 -.132). Being Asian was a positive predictor in two of the four regression while being black was a fairly strong negative predictor in all regressions [b*= (-.083) – (-.064)] when compared to whites.

Once again, family measures that had significant positive coefficients were married (b*=.051-.090), family education level (b*=.074-.089), household size (b*=.029 - .052), and public school (b*=.060 - .048). Joining these positive predictors for the first time were stimulating materials (b*= .047- .054) and parent/child activities (b*=.046). The lone constant negative predictor was parent stress [b*= (-.090) - (-.076)].

Main study groups correlations.

The only main study group with more than one significant coefficient was the LCP group during the kindergarten and first grade regressions (b*= -.046, -.064). LIP had a significant coefficient during first grade (b*=-.041), as did the LNCPB group (b*=-.046).

Trends across all social competence measures.

One issue that must be expressed about the social competence measures is that the proportion of variance explained (R^2) is fairly low for all regressions and especially internalized problem behaviors. Part of this may be that these measures seemed to be fairly subjective. All of these measures were based on the opinions of a child's primary teacher. Internalized Problem Behaviors seem to have more subjectivity because teachers were also asked to infer characteristics such as depression and anxiety. This may have led to higher levels of variance between teachers, overall weakening the predictive ability of the regressions (Internalized Problem Behaviors had the smallest R^2 scores). This amount of subjectivity may be part of the nature of collecting behavioral measures in a study that is not primarily focused on these measures.

Independent predictors' trends:

Despite the problems with the subjectivity, there were some consistent predictors across all of the sets of regressions. Age was an independent variable that stood out. The pattern in all the sets of regressions was that age was a strong predictor at kindergarten and 1st grade, weakening as time went on, so that it had no significant relationship to social competence measures by the end of fifth grade. This seems to fit the research on the benefits of holding children out of kindergarten for an extra year, especially for those from low-income backgrounds (Datar, 2006).

Being female was a strong predictor for all sets of regressions. This was not a surprise for externalizing problem behaviors, interpersonal behaviors, and self regulation since much of the research around behavior in children point to boys as more likely to be labeled as outwardly aggressive/overactive (Skiba, Michael, Nardo, & Peterson, 2002). It was interesting to see female status as a negative predictor of internalizing problem behaviors. One might infer since boys are more likely to have aggressive behaviors, girls would then be seen as having higher level of Internalized Problem Behaviors. This did not played out in the current research as boys were not only more likely to be linked to higher levels of all problem behaviors, external and internal, but also lower levels of desirable behaviors.

When compared with white children, black children had higher levels of external problem behaviors and lower levels of desirable behaviors. On the other hand, Asian children were significantly linked to lower levels of internal and external problem behaviors as compared with whites.

The family characteristics of higher educational levels, being married, parent involvement, and high levels of stimulating materials in the home were all linked to lower levels of problem behaviors and higher levels of desirable behaviors throughout the social/emotional regressions. The main family characteristic that was a predictor of higher levels of problem behaviors and lower levels of desirable behaviors across a majority of these regressions was parenting stress.

The two surprising independents that were consistent predictors across these sets were public school and family size. It was not a surprise that these were predictors but the nature of their relationship to the dependent social/emotional competence measures was not expected. Being a student at a public school was correlated with lower levels of reported external problem behaviors and higher levels of desirable behaviors in kindergarten and 1st grade. A conjecture that can be made is that expectations between public and private schools may vary to a certain degree. For instance, a teacher at a private Catholic school may have dramatically different expectations for kindergarteners' ability to pay attention and stay still then a teacher in a public school. So making all other things equal, children with similar behaviors may have higher reported levels of externalized behaviors in the Catholic school when compared to their public school peers due to the subjectivity of their teachers/schools. Family size in educational research is often linked with lower performance in school, but for social/emotional dependents in this study, they are link with lower levels of external problem behaviors and higher levels of desirable behaviors during the first three observation years (k-3rd grade) in the study. A possible explanation could be that children with more siblings already have experience dealing with other children in their families before formal schooling, thus they have more social competence upon entering school then those of a similar background with less or no siblings.

Main study groups trends.

The main experimental groups (LCP and LIP) along with the low-baseline of LCNPB had spotty patterns of correlations to the dependent social competence measures. When they had a significant coefficient, these groups could be characterized as being correlated with higher levels of problem behaviors and lower levels of desirable behaviors as compared to their middle class counterparts.

Although the null hypothesis could be rejected, the alternative hypothesis that two study groups (LIP and LCP) would have behavioral measures that were close to their middle class counterpart and then fading away as time passed at two different rates could not be accepted. The group that had the most significant beta scores was the LCP group. Since this group appeared much more often as a predictor it can be said that there is a significant difference between the two experimental groups, rejecting the null hypothesis. However, even though this group was a predictor multiple times within most of the sets of regressions, there was no clear pattern of beta scores rising or falling as they moved through the observations in these sets. In addition, since there were not enough significant coefficients for the LIP group, the two could not be compared for levels of fade out between each other. Furthermore, the LCNPB group, who was theorized to have the most differences when compared to the MICB group, actually had the least amount of coefficients that were significantly different to the middle class baseline. Thus, I could not accept my alternative hypothesis that the added income for the LIP group would be linked to less fade out of social competence as compared to the LCP group.

It is not too surprising that the alternative hypothesis was not accepted, as it was a bit of stretch to begin with. Early childhood preschool programs, while providing many other services, are primarily focus on cognitive development in the classroom. And although it can be expected that children may benefit socially/emotionally from partaking in a center-based program and gaining an increase in income in the home, behavior and the ways it is viewed is much more a cultural construct than a cognitive test score. Thus, many other factors outside of the realm of this study most likely contribute to behaviors in the classroom and how they are recorded (e.g. the culture of the teacher). This seems to be supported by the relatively low amount of explained variance (R^2 values) within these social/emotional regressions.

Social Competence as a control.

Although these social/emotional regressions did not adhere to the alternative hypothesis, they were still vital as the attention of the study turned to the main educational measures. Since there were significant differences between the study groups and the middle income baseline in terms of these behaviors, and the fact that behavior can affect cognitive development, it is clear that behavior should also be included as a control variable in the mathematics and reading regressions for this study. And since the LCP group was significantly different from the middle class counterparts much more often than the LIP, not introducing behavior would most likely bias the results of the educational regressions.

Before including kindergarten social competence as a control into the main educational regressions, it was important to vet these measures. The most important test that needed to be run was a correlation matrix. Since the behavior regressions had similar predictors, my concern was that they would be too highly correlated with each other, which in a regression could cause multicollinearity. Also, with the high number of independent controls already added to the regression model, being able to consolidate some of these behavior variables would be beneficial. The results of a correlation matrix between Internalized Problem Behaviors, Externalized Problem Behaviors, Interpersonal Behaviors and Self Regulation are in Table 14.

Table 14

Correlation Matrix for Social Emotional Behavior Variables

		Interpersonal Behaviors	Externalizing Problem Behaviors	Internalizing Problem Behaviors	Self Regulation Composite
Interpersonal Behaviors	Correlation	1			
	Sig. (2-tailed)				
	N	21409			
Externalizing Behaviors	Correlation	-.606**	1		
	Sig. (2-tailed)	.000			
	N	21409	21409		
Internalizing Behaviors	Correlation	-.371**	.305**	1	
	Sig. (2-tailed)	.000	.000		
	N	21409	21409	21409	
Self Regulation Composite	Correlation	.815**	-.675**	-.395**	1
	Sig. (2-tailed)	.000	.000	.000	
	N	21409	21409	21409	21409

**. Correlation is significant at the 0.01 level (2-tailed).

The results of the correlation matrix showed high levels of correlation between Externalized Problem Behaviors, Interpersonal Behaviors, and Self Regulation. This was expected as we have discussed that these measures are all teacher ratings on outward behaviors. Because they were so highly correlated, it can be said that they were measuring the same/similar construct and entering them all in the cognitive regressions could have cause multicollinearity.

Because it was the more comprehensive and seemed to have elements of both of the other external behavior measures, Self Regulation was selected to be part of the educational regressions alongside Internal Problem Behaviors. Self Regulation is a composite variable made of two teacher ratings, self control and approaches to learning. Self control conceptually seemed closely related to Externalizing Problem Behaviors, as the more self control one has, the less problem behaviors one should have. Approaches to learning seemed closely related to Interpersonal Behaviors as they are both looking at the attitude of the child, so that one that is viewed to have good approaches to learning would most likely also have good interpersonal skills.

With the decision made to use kindergarten measures of Internalized Problem Behavior and Self Regulation as controls, the final hurdle was to make sure that they were not too highly correlated with IRT Mathematics and Reading scores, which were the dependent variables for the cognitive regressions. A correlation matrix run for these two measures and all of the IRT scores was conducted and reported in Appendix C. Fortunately, all correlations were low (below .357), supporting their inclusion to the cognitive regressions.

OLS Regressions And Results: Cognitive Skills

The main measures of the achievement gap are cognitive scores. Of the main subjects in school, mathematics and English language arts are view as foundational. Because this study is focusing on the gap between middle and lower class students, it can be argued that although social competence measures could give us further insight, the most important analyses in the current study were the mathematics and reading regressions.

As with the regressions on the behavioral measures, each educational regression was run with the same procedure in SPSS. The only differences between the cognitive and social competence regressions were that behavioral measures were added as controls and that the cognitive measures followed students through another data point in 8th grade (O_5).

IRT Mathematics regressions.

Table 15

MLR Results: IRT Mathematics Tests

Results of OLS Regression: IRT Mathematics Scores: Independent Predictors Standardized Regression Coefficient (b*)					
Independent Variable	**Spring Kindergarten(O_1) n=6363; F=103.161*****	**Spring 1st Grade (O_2) n=6230; F=86.786*****	**Spring 3rd Grade (O_3) n=5366; F=88.795*****	**Spring 5th Grade (O_4) n=4306; F=72.836*****	**Spring 8th Grade (O_5) n=3802; F=55.823*****
Age	.206***	.141***	.068***		
Female	-.107***	-.149***	-.184***	-.184***	-.152***
Asian	.039***				
Hispanic	-.045***	-.039***	-.033**		
Black	-.051***	-.080***	-.114***	-.111***	-.114***
Household Size	-.048***	-.041***	-.055***	-.063***	-.032*
Family Education	.161***	.169***	.187***	.212***	.210***
Public School	-.068***	-.023*			
Rural Setting		-.034**	-.060***	-.057***	-.034*
Financial Troubles	-.028*				
Residential Instability High			.039***	.036**	
Extracurricular Activities	.092***	.081***	.071***	.038*	
Stimulating Materials High	.091***	.086***	.068***	.064***	.071***
Parent Involvement	.030*	.031*			
Internalizing Problem Behavior	-.048***	-.031*	-.036**	-.034*	
Self-Regulation Composite	.239***	.257***	.254***	.258***	.235***
Main Study Groups					
LNCPB	-.073***	-.062***	-.112***	-.135***	-.126***
LCP			-.061***	-.081***	-.093***
LIP			-.039**	-.062***	-.049*
Proportion of Variance Explain (R^2)	.325	.292	.329	.334	.302

*p≤.05; **p≤.01; ***p≤.001

As discussed in chapter three, IRT mathematics exams were created by the ECLS-K researchers to measure math skills in the study's subjects. They borrowed items from many well-know cognitive tests and the reliability of each test was verified and reported by the study managers (Tourangeau, Nord, Sorongon, & Najarian, M., 2009). OLS dummy variable regressions were run for each of the five tests given in the spring of the observation year. The results are included in Table 15.

The inferential statistics of the mathematics regressions illustrated significant and strong models. All F-tests were significant ($p<.001$) and the scores were very high, meaning there was much more variance between the groups than within the groups. Also the proportion of explain variance was high (R^2=.292-.334). The fact that the R^2 scores stayed consistently high throughout the regressions showed the predictive power of the regression using kindergarten controls.

Independent control predictors.

There were many strong predictors within the groups of independent control variables. Most, if not all, were to be expected, especially based on prior research results. Age, gender, and race all played a significant role across this set of regressions. Age was a strong positive predictor in the kindergarten control year (b*=.206), and became weaker in first (b*=.141) and third (b*=.068) grades, finally having no significant relationship to mathematics scores in eighth grade. Being a female student was a consistent negative predictor of IRT mathematics scores throughout the regressions [b*= (-.107) - (-.184)]. This is not a surprise due to the research on learning rates of females and males in mathematics using the same data set (LoGerfo, 2006). Being black or Hispanic were also negative predictors, but in much different patterns. The Hispanic coefficient was highest in the control year (b*= -. 045) and dissipated until there was no significant difference in fifth and eighth grade from their white peers, holding all other controls equal. The black variable had a coefficient similar to Hispanics in the control year (b*= -.051), but instead of dissipating, it strengthened as a negative predictor with eighth grade being the peak (b*= -.114), more than doubling the control beta.

Strong positive family predictors included family education, extracurricular activities, and stimulating materials. Of these, family education had the largest coefficients (b*=.161 - .212). These are all constructs shown to correlate to achievement in school in past research. Strong negatives included rural setting, household size, and attending public schools.

Both behavioral measures added as controls had significant coefficients. Internalized Problem Behaviors was a negative predictor in every regression except the eighth grade measure. The Self Regulation Composite was a strong positive predictor throughout all five regressions. The coefficients stayed much the same in each regression including the control (b*= .235 - .258). These results further supported the inclusion of these behavioral measures, boosting the overall strength of the regressions.

Main study groups correlations.

The results of the main study groups mirrored the alternative hypothesis, ultimately allowing for its acceptance. Reviewing the hypothesis, the low-income no preschool baseline group (LNCPB) was predicted to start as a larger negative predictor than the LCP and LIP groups and stay that way throughout the regressions. This would be due to the fact that those in this group did not benefit from a center-based preschool, nor did they get the extra support of an influx of income early in their k-12 education. Both LCP and LIP would start closer to their middle income counterparts and then fade to become negative predictors as time passed. The difference, and the crux of the study, is that the LIP group (those who went to preschool and whose families had a significant bump in income between kindergarten and first grade) would be less of a negative predictor as compared to the LCP group (preschool, no bump in income) as time passed.

Being a member of the LNCPB group was a negative predictor in all regressions during this study, control and follow-ups. Generally, as regressions moved forward, this group's coefficients became a stronger negative from -.073 in kindergarten to -.126 in eighth grade. This means that holding all controls equal those in the LCNPB group would be predicted to score from 7.3% in kindergarten to 12.6% below the middle class group (MICB) in grade eight on the IRT math test. This growing gap is in line with much of the achievement gap research between middle class and low-income children.

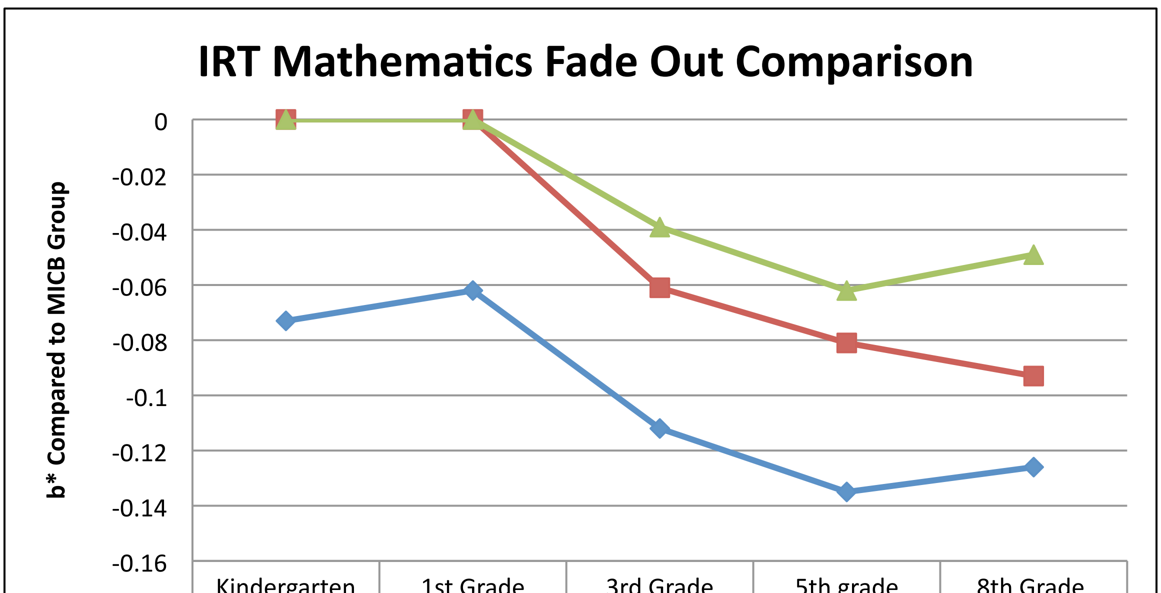
Both the LIP and LCP groups had no significant difference with their middle class peers during the kindergarten control and the first follow-up in first grade. By spring of third grade, however, they did become significant negative predictors, showing fade out of mathematical skills as compared to their middle income peers. They continued to be negative predictors through 8^{th} grade. However, the amount of fade out was different between the groups.

The LCP groups started to fade out in the third grade with a standardized beta of -.061. In terms of the IRT Mathematics test, this means that they would be predicted to score 6.1% lower on average (holding all controls equal) than their middle class counterparts. This coefficient grew to -.081 in fifth grade and finally to -.093, or 9.3% lower than those in the middle class group by eighth grade. The LIP group started fading out in 3^{rd} grade, but with a coefficient of -.039, or 3.9% lower than the middle class group. Then in fifth grade it grew to 6.2% lower. Finally, the standardized beta rose to -.049, or 4.9% lower than the middle class group in eighth grade.

The graph in Figure 7 illustrates the relationship between the two study groups in terms of their differences in fade out. To find the amount of fade out from observation to observation for the LIP and LCP groups, I would have had to use the fade out formula (FO) from Chapter III. However, since the two groups had no significant difference with the middle class group in the control measure (kindergarten), each significant coefficient became the actual FO figure ($0 - b_{xy}$).

Figure 7

Graph of the Fade Out of LIP and LCP Comparison Groups: IRT Mathematics Tests



	Kindergarten	1st Grade	3rd Grade	5th grade	8th Grade
LCNPB	-0.073	-0.062	-0.112	-0.135	-0.126
LCP	0	0	-0.061	-0.081	-0.093
LIP	0	0	-0.039	-0.062	-0.049

As illustrated, the fade out gap between the LIP and LCP doubled. The LCP, which started with the LIP and the middle income comparison group, has slipped closer to the LNCPB to that the LIP. In contrast, the LIP group is much closer to the middle income baseline group (MICB) than the low-income baseline group (LCNPB) and their fade out from the MICB is predicted to be around half of the LCP group's fade out.

The overall predictive strength of the regressions and the patterns of the LIP and LCP, allows me to not only reject the null hypothesis, but also accept the alternative hypothesis for mathematical skills fade out. With R^2 values all near or over .300 the predictive power of the regressions is high for a social science study. The size and difference between the coefficients of the two study groups makes these findings even more interesting. Both groups started with no predictable difference with the middle income group and grew to 4.9% (LIP) and 9.3 % (LCP) difference. In context, with all else equal, that would mean that those in the LIP group would be expected to score nearly half a letter grade lower than their middle class counter parts, while the LCP group would be expected to score almost a full letter grade worse.

IRT Reading Regressions.

IRT Reading tests were created by the ECLS-K in much the same manner as the IRT Mathematics tests. The researchers borrowed items from popularly accepted reading tests to create the IRT, again checking for reliability. The results of the five IRT Reading regressions are in Table 16.

Table 16

MLR Results: IRT Reading Tests

Results of OLS Regression: IRT Reading Scores: Independent Predictors Standardized Regression Coefficient (b)					
Independent Variable	**Spring Kindergarten(O_1) n=6251; F=58.178*** **	**Spring 1st Grade (O_2) n=6178; F=69.620*** **	**Spring 3rd Grade (O_3) n=5347; F=90.731*** **	**Spring 5th Grade (O_4) n=4306; F=72.260*** **	**Spring 8th Grade (O_5) n=3788; F=63.660*** **
Age	.128***	.090***	.065***	.045***	
Asian	.071***	.049***			
Hispanic			-.047***	-.031*	-.065***
Black			-.064***	-.078***	-.119***
Household Size	-.080***	-.074***	-.097***	-.106***	-.059***
Family Education	.170***	.163***	-.194***	.222***	.207***
Public School	-.072***	-.062***	-.039***	-.036**	-.067***
Rural Setting	-.042***	-.066***	-.041***	-.043**	
Parenting Stress	-.031*				
Depressive Symptom	-.028*	-.032*		-.032*	-.046**
Residential Instabil.			.041***	.050***	.039*
Stimulating Material	.071***	.077***	.070***	.048**	.057***
Extracurricular Act.	.068***	.059***	.074***	.048***	
Self Regulation Composite	.214***	.254***	.236***	.233***	.205***
Main Study Groups					
LNCPB	-.045**	-.083***	-.127***	-.128***	-.136***
LCP		-.042**	-.067***	-.076***	-.090***
LIP		-.042**	-.061***	-.058***	-.068**
Proportion of Variance Explain (R^2)	.215	.250	.335	.332	.330

*p≤.05; **p≤.01; ***p≤.001

As with the math regressions, the set of reading regressions had high and significant F-test values throughout (F=58.178- 90.731). The proportion of variance explain by the regressions were also strong (R^2=.215-.335). In fact, R^2 strengthened as the observations went on. This could be interpreted as those starting controls actually becoming stronger predictors as time passed on and the effects of these beginning characteristics blossomed.

Independent control predictors.

The predictors of age and race again were significant in these the reading regressions but gender was not. Unlike mathematics, there was no significant difference between the means of the female group versus the male. Age was once again a strong predictor in the control year and weakened as the observations went forward, disappearing as a significant predictor after fifth grade. Being Asian was a positive predictor in the first two observations. Hispanic and black students both began to separate from their white counterparts in the 3rd grade observation and became strong negative predictors as the observations continued through 8th grade, although black (b*= -.119) was a much stronger negative predictor than Hispanic (b*= -.065).

Consistently strong and positive family predictors were family education, stimulating materials, and extracurricular activities. Strong negative predictors of reading skills were household size, public school, and rural setting. Internalizing Problem Behaviors was not a predictor of reading scores, but Self Regulation once again had significant and strong coefficients throughout (b*=.205 to .254).

Main study groups correlations.

As with the IRT Math scores, the statistics for the IRT Reading regressions both help to reject the null hypothesis and accept the alternative that an increase in income during early childhood for low-income students who attended a center-based preschool helped to slow the fade out of reading skills gained in preschool.

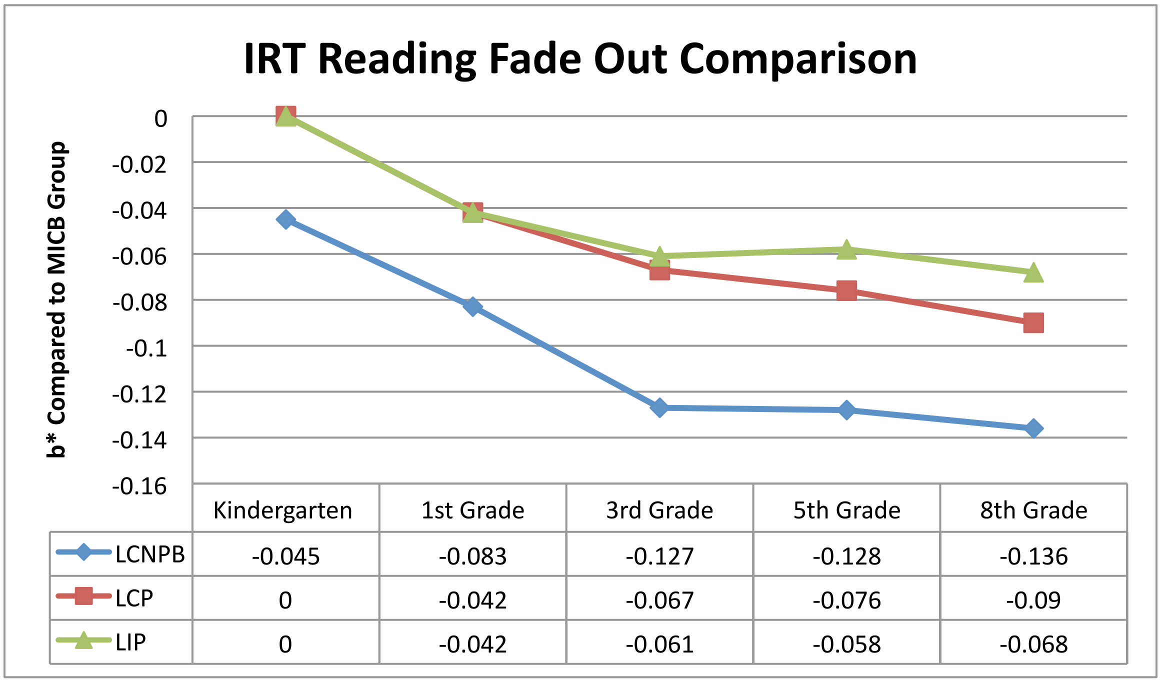
The LNCPB group began as a negative predictor in the control kindergarten year (b*= -.045) as compared to their middle income counterparts. This again was hypothesized because they did not go through a center-based preschool program. As the observations continued, LNCPB became a stronger negative predictor so that by the end of the last observation in eighth grade, the group was predicted to score 13.6% worse in reading than their middle class counterparts. This gap was more than triple the kindergarten difference.

Examining the differences between the LIP and LCP groups, although less dramatic than the mathematics regressions, there was a significant pattern of difference between the groups. Both started out with no significant difference with their middle class peers in the kindergarten control year. By the first follow-up in first grade, they both became negative predictors of reading skills, having identical coefficients ($b^*= -.042$). However, as the observations continued, slowly these two groups began to separate so by the 8th grade observation the LCP ($b^*= -.090$) was a significantly larger negative predictor that the LIP group (-.068). Beginning the same in the kindergarten year and 1st grade follow-up, the LCP was predicted to score 9% lower and the LIP students were predicted to score 6.8% lower that their middle class counter parts, holding all controls equal, by the end of eighth grade. A graph of the relationship between the two experimental groups along with the low-income baseline and the middle class group is shown in Figure 8.

The significant pattern shown in Figure 8 along with the F-values and R^2 scores allowed me to reject the null hypothesis and accept the alternative hypothesis. Indeed, as with the mathematical skills, those student of low-income who attended a center-based preschool and whose families experience an influx of income over $5,000 between kindergarten and first grades did not fade out as much as those of the same background who did not experience such an income boost.

Figure 8

Graph of the Fade Out of LIP and LCP Comparison Groups: IRT Reading Tests



	Kindergarten	1st Grade	3rd Grade	5th Grade	8th Grade
LCNPB	-0.045	-0.083	-0.127	-0.128	-0.136
LCP	0	-0.042	-0.067	-0.076	-0.09
LIP	0	-0.042	-0.061	-0.058	-0.068

Secondary Educational Models.

Although there were enough subjects in each study group for the main educational regression models, there were not enough to run secondary regressions. As discussed in Chapter III, these secondary regressions would be identical to the primary regressions, only the groups would be crossed with other variables such as race, gender, or differing income gains. Because the proposed secondary models are even more exclusive than the primary study groups, fewer individuals from the sample would be selected for the groups. These groups would not be large enough, especially with such a high amount of control variables. For example, when the LIP group was crossed with race, the black LIP group's numbers fell to 89 in the control year. If attrition rates were similar to the primary groups, that would leave around 40 subjects for the 8th grade measure, too small for the amount of variables in the model. Although I could not justify running these regressions with the current number of subjects, these are worthwhile and insightful cross connections that should be studied in the future. A more thorough discussion of this topic occurs in Chapter V.

Summary.

Taking in all sets of regressions, an increase in income for low-income families during early childhood for those children who attended a center-based preschool is a predictor for the retention of cognitive skills. Although there were many significant differences between the experimental groups and the middle income baseline group during the social competence regressions, there was no pattern that would delineate the two (LCP and LIP). Because of this, no claim can be made about how this treatment may affect social competence in school. However, with both sets of cognitive skills regressions, a clear pattern arose between the LCP and LIP groups in the context of the two baseline groups. The strength of both sets of regressions and the relatively large differences between the two groups allow for the claim to be made that this increase in family income of at least $5,000 between kindergarten and first grade for low-income children who attended a center-based preschool is correlated with less fade out of cognitive skills gained in preschool. These results lead to a discussion of the limitations and implications of this study, as well as its effects on future research into this subject.

CHAPTER V

DISCUSSION AND IMPLICATIONS

Although the current study has shown strong evidence linking an increase in family income during early childhood for low-income students and the reduction of fade-out of preschool gained skills, it is important to again discuss its limits. After those limitations are highlighted, I will discuss the study's future directions and implications.

Limitations.

In Chapter III, a longer discussion is had on the limitations and threats to validity due to the design of the study. History, selection bias, the shortcomings of the ECLS-K survey, and those inherent restrictions of multiple regression analysis still hold true. Beyond these, a few of the limitations as they relate to the scope and use of the study are reiterated below before a discussion of the implications is presented.

Examining economic capital exclusively.

The theoretical groundings of the study indentified three types of capital (cultural, social, and economic) and their possible effects on the retention of educational skills for low-income students. Though evidence within the literature review supports the assumption that all three types have effects, the focus of this research project was on a change in economic capital. As a result, no direct claims can be made about the role a change in cultural or social capital, in or out of relation with economic capital, has on retention of preschool skills for low-income students from this research.

Low-income only.

This study only targeted those students who came from low-income families. Other low-income subgroups were not included and no attempt was made to connect the phenomenon to other income groups. Race, gender, and other subgroups within the study groups could have added another layer of analysis to the study. Unfortunately there were not enough subjects in the LIP and LCP groups to be able to create these cross-groups. Because of this, the results of the study speak to children of low-income families as a whole.

Increase at $5,000.

The study used a $5,000 increase in income as a cut-off point, so differentiating between amounts of increases in income and possible differing affects on fade out is not within scope of this study. Crossing different amounts of income increases was going to be a set of secondary regressions but as with other subgroups, the sample size was not big enough to further categorize by levels of increase in income. Any debate about the most effective amount of increase in income or a more specified timing of such increase will be left up to future research.

Types of income increases.

It can be hypothesized that employment or higher levels of employment may be most effective type of income increase due to the prior research on cultural capital and the lessening of isolation that comes with employment. However, the current study does not differentiate between increases in income that come from employment and those that come from other means such as government programs. For that reason, no claims can be made as to the type of increase in family income that may link to better retention of academic skills gain in preschool.

Generalizability.

Since the study groups were from a specific subset of the ECLS-K study and not randomly formed, the generalizability of the study technically only applies to this particular cohort of students. Despite the amount of rigorous controls and the use of weights, this inherently increases the risk of type II error when applied to other cohorts of students, even those from low-income backgrounds. As discussed in Chapter III, the current study prioritizes internal validity over generalizability. It was important to examine if this increase in income could be linked to less fade out, as this had not been tested before. Future research will help support or reject the reproducibility of the findings to other settings and time periods.

Does not answer the "why".

Despite the strong relationship between decrease in fade out of those children who went through a center-based preschool program and whose family had an increase in income, why this relationship exists is not fully answered in this study. Again, regressions results are correlations and thus, cannot speak to the nature of relationships. The context, circumstance, and prior research can shed light on the "why", but further research aimed at digging into this topic would be better able to explain the phenomenon going forward.

Future Explorations.

A natural pivot from the limitations of the current study is a discussion on how future studies can fill some of the research gaps left behind. Although this paper illuminates a relationship between increase in income for low-income families of children who attended a center-based preschool and the lessening of fade out, much more remains to be uncovered. Beyond replicating this study to different data sets and contexts, other aspects surrounding this relationship should be examined. These include studying the effects on different low-income subsets, mediator analysis, and describing the phenomenon through qualitative studies.

Testing different subsets.

One initial aim of the current study that could not be explored was testing the hypothesis on different subsets of the population. As discussed in Chapter IV, there were not enough subjects to run a multiple regression analysis for specific groups within the low-income population in the ECLS-K. Testing the study's alternative hypothesis with race, gender, differing levels of income increases, differing timings of income increases, and many more cross variable relationships would certainly add more depth to the topic.

To be able to create studies with this degree of specificity, data sets that over sample or center on low-income children and families will need to be utilized or created. Ideally, this would be a random survey examining children in low-income families during early childhood with background, educational, and parent measures included. This may be a huge challenge seeing as the current study used a national survey with over 21,000 children and was only able to create an increase in income study group (LIP) of a few hundred. Other sources of data could be programs designed to employ individuals with young children, which, while not random, could include enough subjects who have had a change in income to create subsets. Whatever the source, the challenge will be to get enough low-income families who have been economically mobile and are connected to all the other key educational and family level variables.

Finding the mediators of income increases.

Clearly it is not the actual dollar bills that account for the differences between the LIP group and the LCP group; rather it is what that money does for a family. The mediators of an increase of family income were not the focus of the current study. While there is plenty of research (much of which is discussed in Chapter II) that discusses the effects of income, future explorations in to this topic should include an analysis of the path leading from an increase of income to a decrease in the fade out of preschool gained skills. Quantitatively, this could take the form of methods such as structural equation modeling. Other ways of examining this may be through qualitative methods.

Using qualitative research to help answer "why".

Along with tying the mediators of an increase of income for children in low-income families who went through a preschool program and the decrease in fade out, qualitative methods could give more context as to why this increase has its effects. For example, in-depth case studies comparing a few families from the population of interest could be used to illustrate the mechanisms at play when income increases during early childhood for children in poverty and what may account for their ability to retain preschool gained skills. The overall flexibility of qualitative studies could allow for different subsets, income levels, and amounts of income increases to be addressed and described in ways not possible in quantitative research.

Implications.

Despite the limitations of the study and the need for further research into the topic, the results have strong implications for researchers, practitioners, and policymakers. Being able to show the links between increase in income for low-income families whose children go through center-based preschool programs and the retention of those preschool skills through a wide range of studies would certainly bolster the connections made in the current study. But if we are to ultimately accept these findings, they call for changes in action for all stakeholders.

Implications for researchers.

Increase in income as a metric.

If the results of this study are to be accepted, education researchers may need to consider a new metric when dealing with the subjects of fade out and achievement. In the past, most researchers of education achievement have used income as a marker variable to categorize children. This study shows that income does not have to be a static measure and, in fact, a change in income is a predictor in a cognitive achievement analysis of low-income children who have gone through a center-based program. Those that ignore or do not include this variable in their analyses may be biasing their results, especially when examining this subset of the population.

Timing of a change in income.

In addition to considering change in income as a variable, those that may study the effects of an increase of income on educational measures should consider the timing of that income increase. The results of this study, as compared to other income/education studies, suggest that the timing of an increase in family income does matter. In the current study, the increase in family income comes during early childhood (between kindergarten and first grade) and is a positive predictor of the retention of skills. Other studies (Morris, Duncan, & Clark-Kauffman, 2005; Morris & Gennetian, 2003) have shown that increases in income later in a child's life can actually have a negative effect on educational achievement scores as compared to peers.

Implications for practitioners.

Helping parents in early childhood.

For those that work with children and families during early childhood, this study may signal a need to put some emphasis on helping parents with employment. Both in anecdote and in formal research, students from stronger family backgrounds often perform better in school. And although this study does not focus on the mediators of income in the family, prior research makes it clear that an increase in income can benefit many parts of family life. Because practitioners do not have the power or resources to give families in poverty money, linking with or creating job programs and networks for unemployed or underemployed parents of children in early childhood may be mutually beneficial. This could help create stronger families with more resources, in turn helping low-income children keep better pace with their middle class peers in schools.

Expanding from a strict focus on outside mediators of poverty.

Often the focus of practitioners is on the mediators of income that they can control. Giving material goods and free access to programs is often the response to issues of poverty but, in many cases, may not be enough. In the case of this study, both of the low-income experimental groups came from similar backgrounds and most likely similar experiences and access to resources. Yet those in the LIP group were connected to less fade out. One way to explain this is that while programs and charity may come and go, a permanent increase in income allows for constant benefits over years. In addition, there are negative aspects of poverty that may not be alleviated by simply easing some material hardships as it pertains to children's schooling, such as depression and parenting stress within the home. Increasing income may allow the family unit to become a more constant and holistic source of support, not dependent on the whims of budgets, grants, and others' generosity.

Implication for policymakers.

Focus on both education and family income during early childhood.

Policymakers grappling with the achievement gap need to consider not only early access to quality education for low-income children through center-based preschool but also the financial health of the families that these children come from if society is to get the most "bang for the buck". Researchers have already shown the long-term cost/benefits of providing this population of children early childhood education. From the results of the current study, further investment during the same time for parents should boost these returns even further. This is added to the fact that the capital needed by those in power, in many cases, may involve more political will than financial investment. For instance, increasing the minimum wage and enticing private industry to reach out to parents of young children would not require the government to open its coffers.

Possible cost-benefit.

On top of the low financial cost of some solutions, an argument can be made that even those programs that require substantial monetary investment would actually save money in the long-term. This has already played out in the cost-benefit preschool research. Billions of dollars are spent by society on prisons, welfare, and other social programs, and this does not including the amount of money spent on trying to bridge educational gaps students display during middle and high school. Therefore, the cost of any small dent in student fade out due to societal investment around issue of family income may be off-set by a big dent in future societal expenditures.

Effects on political capital.

Finally, in an era of non-stop campaigning for politicians and others in positions of power, often things that could make the most lasting change are not politically prudent. An example of this is the prior cost-benefit preschool research. Most of the gains are only evident when children in these programs are adults. This causes decades of gaps between those that make the expenditures and the fruits of the societal sacrifice. Fortunately, during the Civil Right Era, in which many of these preschool programs were created, equity was at the forefront of the national dialogue.

There are very few, if any, quick technical fixes to major societal problems. Yet, elected and appointed officials in the current era often live with impatient constituents, especially when it comes to government spending. Therefore, it takes a lot of political courage to advocate for programs and policies whose effects can only be measured long after the next election cycle.

The current study, while certainly not advocating a quick fix, allows for the illustration of gradual returns in a relatively short amount of time. The gap between those in the LCP group and the LIP group was significant in both mathematics and reading by the third grade, or three years after the treatment. This creates a situation beneficial to society, families, and children, while also giving policy makers tangible results to move forward with. Using this lens, supporting policies that would increase income for low-income families in addition to early childhood education may be advantageous to a policymaker's career.

Final Summary.

Quick Overview.

Gaining incite from numerous income and preschool researchers, I was able to identify that children in low-income families who have attended a center-based preschool often lose the academic advantage they gained during preschool as they move through k-12 education. Through the use of Bronfenbrenner's ecological theory, Bourdieu's capital theory, and Risk Factor Theory, I was able to create a framework to explain why this may be happening; namely, that material and psychological effects of poverty did not allow families to give the support that would maintain this growth. Treating income as a causal risk factor instead of a marker factor, I crafted a research question to examine what would happen with these preschool gains if family income were to increase during early childhood. I hypothesized that this increase in income would help children retain more of their preschool skills by mediating some of the effects of poverty in the family, and that early childhood was the best time to introduce this income increase since this is when children are highly nested within the family unit. Using the ECLS-K data set, I was able to create a study to test this hypothesis. I created an ex post facto, quasi-experimental study with two comparison groups of children who both went through a center-based preschool and were from low-income families. One group gained the "treatment" of an increase in income during early childhood (LIP), while the other stayed consistently in their low-income bracket (LCP). With numerous background control variables and a middle class group (MICB) and a low-income no preschool baseline group (LCNPB) for comparison, I was able to use multiple regression analysis to test whether this treatment of an increase in income would help the LIP group members retain more of their preschool skills that the LCP group as they moved from kindergarten to 8^{th} grade. Before the main dependent cognitive measures (math and reading scores) were examined, regressions on social competence were run to test the hypothesis on these skills and to examine if these behaviors should be added to the cognitive regressions as controls. Although the pattern of the social competence regressions did not support the research hypothesis, behavior scores were added as controls to the academic regressions. The results of the academic regressions showed that the LIP group was correlated with around half of the fade out as compared to the LCP group by eighth grade. The acceptance of the research hypothesis led to many implications for researchers, practitioners, and policy makers as well as opened the door to future exploration into the subject.

Closing Remarks.

In closing, this study illustrates the interplay between societal systems and socioeconomic achievement gaps. It calls for a fundamental change in the way we view the connections of these systems if we are to slim educational gaps relating to poverty. The results suggest that we cannot treat education in a vacuum when we know that family economics so strongly predicts educational achievement. There are examples of successful boundary spanning efforts in the recent history of education in our country. Years ago many believed that it was solely the responsibility of families to prepare children for grade school education. Yet, we as a society have shifted our expectations so that it is accepted that children from low-income backgrounds should have access to quality preschool. We have seen these efforts grow as far as full service and community schools with numerous wrap-around family services.

The fight for economic justice should be a major part of educational reform. We often view education as the cure to economic prospects, but the current study illustrates that addressing economic prospects can improve achievement in education. Reforms only aimed at the school building, teachers, and those mediators of family poverty exclusively in the control of researchers, practitioners, and public officials are paternalistic at best and disingenuous at worst. Empowering families through economic opportunity, side by side with early education, can allow for lasting support for children in poverty; remembering that a family unit is a child's first, most consistent, and most influential teacher.

We all hold stakes in this endeavor. Educational researchers may need to shift how they treat income as a variable. Policymakers may need to refocus on global policies that would help the economic prospects of families with young children. Practitioners may need to be open to programming that, although may not be directly linked to children, may ultimately have the greatest effects on their education. We have made an important shift when it has come to the preschool education of low-income children, but what about the economic health of their families? It is the elephant in the room and we ignore it to the peril of our values of justice and equity in our schools and societies.

APPENDIX A

SOCIAL COMPETENCE MEANS AND CASES OF MAIN INDEPENDENT GROUPS

Internalized Problem Behaviors			O_1	O_2	O_3	O_4
Pooled	LCNPB	Mean	1.6375	1.7278	1.7437	1.6820
		N	451.2	371.8	247.2	233.6
	MICB	Mean	1.4890	1.5067	1.5263	1.5334
		N	5161.6	4560.6	3798.4	3427.2
	LCP	Mean	1.7232	1.7043	1.7659	1.7788
		N	548.2	476.2	307.2	271.6
	LIP	Mean	1.6426	1.6477	1.7948	1.7931
		N	278.2	232.2	149.4	134.6
	Total	Mean	1.5260	1.5437	1.5635	1.5669
		N	6439.2	5640.8	4502.2	4067

Externalized Problem Behaviors			O_1	O^2	O_3	O_4
Pooled	LCNPB	Mean	1.7558	1.8031	1.8022	1.7118
		N	451.2	377	250.8	236.2
	MICB	Mean	1.5749	1.5468	1.5734	1.5387
		N	5161.6	4571.4	3818.6	3445.2
	LCP	Mean	1.9046	1.9075	1.9597	1.8124
		N	548.2	479.4	311.4	282.4
	LIP	Mean	1.8267	1.8129	1.9178	1.8298
		N	278.2	234.8	151.4	136.4
	Total	Mean	1.6265	1.6055	1.6241	1.5772
		N	6439.2	5662.6	4532.2	4100.2

Interpersonal Skills			O_1	O_2	O_3	O_4
Pooled	LCNPB	Mean	2.9392	2.9656	2.8706	2.9519
		N	451.2	373.8	246	230.2
	MICB	Mean	3.2318	3.2261	3.2299	3.2175
		N	5161.6	4564.6	3787.2	3406
	LCP	Mean	2.8548	2.8655	2.8180	2.8515
		N	548.2	474.2	310	275.2
	LIP	Mean	2.9449	2.9510	2.9003	2.9180
		N	278.2	234.6	151.2	134.8
	Total	Mean	3.1668	3.1671	3.1707	3.1675
		N	6439.2	5647.2	4494.4	4046.2

Self Regulation Composite			O_1	O_2	O_3	O_4
Pooled	LCNPB	Mean	2.9609	2.9201	2.9072	2.8047
		N	451.2	380.8	251	241.6
	MICB	Mean	3.2834	3.2499	3.2861	3.1896
		N	5161.6	4598	3832	3471.2
	LCP	Mean	2.8633	2.8287	2.8371	2.6733
		N	548.2	482.8	312.8	289.2
	LIP	Mean	2.9381	2.9245	2.9062	2.7476
		N	278.2	234.8	151.6	140.6
	Total	Mean	3.2102	3.1788	3.2216	3.1161
		N	6439.2	5696.4	4547.4	4142.6

APPENDIX B

NORMALIZED AND DEFF NORMALIZED WEIGHTS

- Normalized Weight= Raw Weight (C2 sum)/ Mean Weight
    - Normalized Weight= 3,863,510/181.727
        - C2 Normalized Weight = 21,260
- DEFF Normalized Weight = Normalized Weight (C2) / DEFF (C2)
    - C2 DEFF Normalized Weight= 21,260/4.64
        - C2 DEFF Normalized Weight (sum)= 4582.18

Descriptive Statistics For DEFF Normalized Weight

	N	Minimum	Maximum	Sum	Mean	Std. Deviation
C2 CHILD-PARENT-TCHER WEIGHT FULL SAMPLE	21260	.00000	918.88887	3.86351E6	181.7267971	129.24264402
Normalized weight	21260	.00	5.06	21260.00	1.0000	.71119
DEFF Normalized_weight	21260	.00	1.09	4582.18	.2155	.15328
Valid N (listwise)	21260					

APPENDIX C

COGNITIVE DEPENDENT VARIABLES AND SOCIAL COMPETENCE CONTROLS: CORRELATION MATRIX

Correlations

			INTERNALIZING PROBLEM BEHAVIORS	COMPOSITE SELF-REGULATION	C2 RC4 MATH IRT SCALE SCORE	C4 RC4 MATH IRT SCALE SCORE	C5 RC4 MATH IRT SCALE SCORE	C6 RC4 MATH IRT SCALE SCORE	C7 RC4 MATH IRT SCALE SCORE
Pooled	INTERNALIZING PROBLEM BEHAVIORS	Pearson Correlation	1	-.395**	-.190**	-.183**	-.180**	-.179**	-.162**
		Sig. (2-tailed)		.000	.000	.000	.000	.000	.000
		N	21409	21409	19649	16635	14374	11274	9285
	COMPOSITE_SELF-REGULATION	Pearson Correlation	-.395**	1	.353**	.348**	.346**	.338**	.329**
		Sig. (2-tailed)	.000		.000	.000	.000	.000	.000
		N	21409	21409	19649	16635	14374	11274	9285

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

Imputation Number			INTERNALIZING PROBLEM BEHAVIORS	COMPOSITE SELF-REGULATION	C2 RC4 READING IRT SCALE SCORE	C4 RC4 READING IRT SCALE SCORE	C5 RC4 READING IRT SCALE SCORE	C6 RC4 READING IRT SCALE SCORE	C7 RC4 READING IRT SCALE SCORE
Pooled	INTERNALIZING PROBLEM BEHAVIORS	Pearson Correlation	1	-.395**	-.158**	-.170**	-.166**	-.157**	-.145**
		Sig. (2-tailed)		.000	.000	.000	.000	.000	.000
		N	21409	21409	18937	16336	14280	11265	9225
	COMPOSITE_SELF-REGULATION	Pearson Correlation	-.395**	1	.309**	.349**	.354**	.339**	.328**
		Sig. (2-tailed)	.000		.000	.000	.000	.000	.000
		N	21409	21409	18937	16336	14280	11265	9225

**. Correlation is significant at the 0.01 level (2-tailed).

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