5-24-2009

Asset trajectories and child outcomes: Implications for asset-based policies

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ASSET TRAJECTORIES AND CHILD OUTCOMES: IMPLICATIONS FOR ASSET-BASED POLICIES

by

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A dissertation presented to the
Graduate School of Arts and Sciences
of Washington University in
partial fulfillment of
the requirements for the degree
of Doctor of Philosophy

August 2009
Saint Louis, Missouri

Acknowledgements

It is said that it takes a village to raise a child. I believe the same can be said about getting a doctoral student through the Ph.D. program. Without the support of various faculty and staff members at the Brown School of Social Work, and from friends and family, this dissertation would not have been possible.

I would especially like to thank my advisor and co-chair of my dissertation committee, Michael Sherraden. It has been such a privilege to work with one who is not only vested in the intellectual and professional development of his charges, but also invested in the overall well-being of our families. Michael, despite his hectic schedule, stood in as the honorary ‘granddad’ during my boys’ grandparents’ day at school, and honored us when he and his lovely wife, Margaret, became the god-parents to our baby girl.

I am also indebted to Ramesh Raghavan, my other co-chair, for his extraordinary patience, encouragement, insights, and guidance through this process. His meticulous attention to detail while having a firm grasp of the big picture helped refine and improve this dissertation to a great extent. I would also like to acknowledge and thank Melissa Jonson-Reid, Shanta Pandey, Ed Spitznagel, and Carol Woods for their time, advice, and invaluable inputs. They brought their unique perspectives, which helped to clarify and strengthen the work.

I would also like to thank my fellow doctoral students Paul Sacco, Ben Alexander-Eitzman, and Yung Soo Lee for their statistical and technical assistance in getting the models to run. Paul had also to endure my bouncing of ideas off him for this and other collaborations, and for this as well as the friendship he and his wife Kathy extended to our family, I am grateful.

I would like to especially acknowledge and thank my beautiful and supportive wife, Boon Ping, without whom I would be a lesser man. Boon Ping gave up her career to support my decision to come to the States for this program. While here, she took care of our children and attended to all household matters so that I could focus fully on my studies. This dissertation is due as much to her efforts as it is mine. I would also like to thank our families back in Singapore and Australia for their love, concern, support and encouragement through the years.

Finally, Jonathan, Benjamin and Kaitlyn, this dissertation is for you. May it inspire you to pursue your own one day. And yes, daddy is now finally a doctor.

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I Introduction

Education has long been viewed as the primary key to socio-economic success and an important pathway to social mobility (Haveman, Wilson, & Wolfe, 1998; Morgan & Kim, 2006). In our society today, the economic returns of schooling are rising (Mare, 1995). Success in school is increasingly valued and viewed as a primary determinant of adult independence (Taylor, Clayton, & Rowley, 2004) and as an important channel to socioeconomic success (Goyette & Xie, 1999). A child's educational achievement or human capital development is therefore recognized as being one of the most important predictors of his or her future economic well-being and social mobility (Haveman & Wolfe, 1994; Keeley, 2007). However, in 2005, approximately 3.5 million 16- through 24-year olds, or 9.4 percent of those in this age range in the United States, were not enrolled in or had dropped out of high school, with Hispanics having the highest status dropout rate at 22.4 percent followed by African American at 10.4 percent (National Center for Education Statistics, 2007). Globally, the picture is just as gloomy. According to the United Nations (2007), more than 30 percent of primary school age children among the bottom two wealth quintiles in developing regions are not enrolled in school.

Wealth is increasingly being recognized as an important determinant of children's human capital trajectories. With the availability of wealth data in the past two decades, researchers are finding that explanatory models of children's outcomes that do not include assets or wealth to be inadequately specified. In today's globalized knowledge-based economy where the labor market is less stable, having an income by itself is often insufficient in providing for and enhancing the well-being of individuals. To succeed in the post-industrial economy, people must be able to continually invest in themselves and expand their capabilities. The availability of wealth enables individuals to do just that.

Children's educational outcomes are inextricably linked to public policies. Tobin (2004) opined that the United States is failing its children, with millions of children left behind with substandard child care, health care, housing, education and training as a result of the current political and economic climate. This is because during the last 20 years, and especially in the last 10, tax cuts and market mechanisms have been the main instruments used to create economic incentives for families to invest in their children. But because many of the children most in need of investment live in low- or moderate-income families who pay little or no income tax, these mechanisms often leave them behind (Tobin, 2004). Others have similarly suggested that income maintenance and transfer policies are likewise inadequate in improving the life chances of children

(Sherraden, 1991). While these serve an important function as a safety net, they do little to get the poor onto the ladder of development.

In recent years, there is a shift in the focus of social policies around the world, from the traditional social welfare/social security model of income support to social investment and wealth creation. There is also increased interest among policy makers in assets as an intervention tool to increase the welfare of children and families. A number of asset-based policies aimed at enhancing the developmental outcomes of children, especially those from lower income families, have been implemented or proposed (Loke & Sherraden, 2009). These policies are generally targeted at increasing the human capital of children. However, the development and implementation of asset-based interventions and policies have outpaced the theoretical and empirical developments in the asset approach.

Much of the earlier empirical work on asset-based interventions focused on the technical aspects of implementation rather than on theoretical development and testing (Midgley, 2003). While there is a growing body of research that supports the association between assets and children's educational outcomes, a large proportion of this research is based on cross-sectional studies rather than longitudinal designs. Moreover, the majority of studies examined the association of assets held at a single time point on children's outcomes at a later time. Information about the mediating pathways of the effects of assets, or about whether the timing of asset accumulation matters, is also scarce. Consequently, a number of theoretical questions have not yet been adequately addressed, leaving asset-building policies with thin theoretical and empirical support. Further development of the empirical and theoretical base is critical in informing asset-based policies aimed at helping families accumulate assets for investment and developmental purposes.

It is suggested that assets could be experienced in a number of dimensions, viz., possession, the process of accumulation, and consumption (Paxton, 2001). Little, however, is known about the patterns of asset accumulation over time. This study adds to the assets knowledge base by using a longitudinal design to explore and describe how assets in the household change over time, controlling for a host of socioeconomic determinants (research aim 1).

While studies have suggested that higher asset holdings are associated with better child outcomes, there is a dearth of research on whether an increase in family financial assets, not just asset holdings, is positively associated with better children's outcomes. In addition, little information is available on whether the different asset accumulation trajectories are associated with different educational outcomes for children. For example, would an increasing growth trajectory in family assets be associated with better outcomes compared to those with relatively flat growth trajectories among children from less economically advantaged households? And how would these children compare to those with higher initial asset holdings, irrespective of subsequent asset growth trajectories? There is therefore a gap in research on the effects of assets on children's outcomes from a dynamic perspective. That is, whether increases in assets over time lead to improvement in child outcomes, especially for those from families with lower initial asset levels. This, after all, is the basis for asset-based interventions - to generate the associated positive effects of assets through increasing the assets held by people over time. This study attempts to address this gap by examining if asset trajectories reflecting increases over time are associated with better child educational outcomes as has been found for cross-sectional measures of asset possession (research aim 2).

While the theory of assets effect suggests that assets lead to positive economic, psychological and welfare outcomes, it does not specify the mechanisms by which the effects of assets are played out. Previous research has also generally not focused on possible mechanisms but on demonstrating the independent effects of assets beyond income. Consequently, little is known about the possible pathways through which an increase in assets leads to improvement in child outcomes. Shobe and Page-Adams (2001) suggest that the assets effect is mediated by one's future orientation. Earlier research also suggests that the effects of parental wealth may be mediated by higher parental expectations of their children's educational outcomes (Zhan, 2006; Zhan &

Sherraden, 2003), by better and more stimulating home environments (L. A. Campbell, 2007; Orr, 2003), or by children having higher aspirations for their own education (Destin & Oyserman, 2009; Elliott, 2009). It is not known if these mediated pathways are the same for the different asset trajectories. This study extends this line of inquiry with a longitudinal design to explore potential mediating pathways between assets and children's educational outcomes across the different asset trajectories (research aim 3).

Finally, the child development and poverty literature suggest that there may be critical time windows for healthy development, and that the experiences of poverty at different time periods have different effects on children's outcomes. It is reasonable to infer that the effects of assets may also be different depending on when during the child's life course the asset experience occurs. There are no studies known to the author that explore this question. This study will explore whether there is a difference in high school graduation rates when children experience asset accumulation during early childhood compared to those who experience accumulation only in middle childhood (research aim 4).

In order to better inform practice and policy, more research is needed to empirically test, support, and refine the theoretical propositions of the theory of welfare based on assets. This is especially so with regard to if and how the process of accumulating assets improves child outcomes. This, after all, forms the basis of many of the asset-building policies that have been proposed or implemented. In addition, there is a need to identify the possible mechanisms through which the asset effect plays out. Whether assets have different effects based on the timing in the life course would also need to be explored so as to effectively target the intervention. These issues have important policy implications and impinge on the ability to formulate asset-building policies that maximizes the asset effects while optimizing the use of scarce resources.

This study will address these issues using a series of structural equation modeling techniques, including growth mixture modeling, to examine the effects of parental asset accumulation trajectories on children's PIAT math and reading scores at third grade, and children's odds of high school graduation. In addition, the study will examine whether the effects of asset accumulation are mediated by home environment, parental expectations or by children's aspirations. It will also examine whether the timing of asset accumulation matters. The recent availability of wealth data spanning 20 years in the National Longitudinal Survey of Youth 1979 (NLSY79) Mother and Children datasets will enable the examination of the effects of asset accumulation spanning the entire span of a child's life from birth to age 19-20 for the first time.

II The Theory of Welfare Based on Assets

An emergent area of inquiry into social welfare policies and the effects on children's educational attainment, among others, is the assets perspective (Government of Canada Policy Research Initiative, 2003; OECD, 2003; Sodha, 2006; The Allen Consulting Group, n.d.). The assets perspective views household financial welfare as a long-term, dynamic process rather than as a cross-sectional financial position. It asserts that assets capture this long-term, dynamic quality better than income because assets reflect lifetime financial accumulation or wealth (Sherraden, 1991). In addition, the assets theory proposes that household financial welfare is more than being about consumption, and that assets yield important effects beyond consumption. Assets yield a variety of psychological, social and economic effects, above and independent of the effects of income (Paxton, 2001). It is theorized that the ownership of assets has a strong impact on the choices people make and their life opportunities (The Allen Consulting Group, n.d.).

Assets and income are conceptualized differently in this theoretical orientation. Income refers to the flow of resources in the household that could be consumed to provide the household with daily necessities such as food, shelter and clothing. Assets on the other hand refer to the storehouse of resources built over time (Sherraden, 1991). Income and assets both refer to resources, and differ only in the frame of reference of time. If resources received as income are not immediately consumed, then they become assets (Schreiner, 2004). Assets are also regarded as a special form of money not used for the purchase of life necessities, but used to create opportunities, secure a desired stature and standard of living, or transfer class status along to one's children. Assets, hence, signify command over financial resources, and are particularly important indicators of individual and family access to life chances (Oliver & Shapiro, 1995).

As Sherraden puts it, assets matter because "people think and behave differently when they are accumulating assets, and the world responds to them differently as well" (Sherraden, 1991, p. 148). Specifically, assets improve economic and household stability; create long-term thinking and planning, and connect people with a viable, hopeful future; stimulate development of human and other capital; enable people to focus and specialize; provide a foundation for risk taking; yield personal, social, and political dividends by increasing personal efficacy and sense of well-being as well as increasing social status and social connectedness; and enhance the welfare, well-being and life chances of offspring (Sherraden, 1991). These important psychological and social effects are not achieved in the same degree by receiving and spending an equivalent amount of regular income.

Economic Effects of Assets

It is proposed that assets yield a variety of economic effects. Page-Adams and Vosler (1997) for example, in a study of 193 laid off autoworkers, found significantly reduced perceived economic strain among those that had assets in the form of homeownership, controlling for income and education. Assets have also been positively associated with the economic well-being of women after marital disruption (Cho, 1999), and with single mothers' ability to maintain their families above the poverty level when they had savings (Rocha, 1997).

In addition, Page-Adams and Sherraden (1996) noted in their review of literature that assets appear to increase economic security of families, be they on public assistance, or in female-headed families (Cheng, 1995). Participants in the Individual Development Account (IDA) programs of the American Dream Demonstration, the first asset-based policy demonstration in the U.S., also reported feeling more economically secure as a result of having savings (McBride, Lombe, & Beverly, 2003b). The effect of assets on economic security has also been found in other countries. For example, the accumulation of assets through the Central Provident Fund in Singapore has been reported to improve the economic well-being of Singaporeans (Sherraden, Nair, Vasoo, Ngiam, & Sherraden, 1995).

Assets have also been proposed to stimulate the development of human and other capital, and the data from the American Dream Demonstration appear to support this proposition. Of the 92 approved matched withdrawals from IDAs, 33 percent were used for micro-enterprise, 27 percent for home purchases, 20 percent for home repairs, 13 percent for post-secondary education, and 3 percent for job training (Sherraden, 2000). In another survey of IDA participants' perceptions, 60 percent of those surveyed reported that they were more likely to make future educational plans for themselves and their children as a result of IDA participation (McBride, Lombe, & Beverly, 2003a).

Psychological Effects of Assets

It is suggested that assets connect people with a viable, hopeful future and increase personal efficacy. Without an orientation toward the future, "hope does not thrive, visions are not created, plans are not made, and struggle and sacrifice are not undertaken" (Sherraden, 1991, p151). Having assets can begin the orientation toward the future, which in turn shapes opportunity structures that are quickly internalized. Having assets in itself also create a cognitive reality, a schema, such that people begin to think in terms of assets, its present effects and future consequences. This is because assets are long term in nature, and they connect the present with the future. In addition, assets allow for greater prediction, flexibility and control over one's life. Yamada and

Sherraden (1996), analyzing the Panel Study of Income Dynamics data from 1968 and 1972, found that assets did indeed have the hypothesized causal effects on one's future orientation and personal efficacy, with assets leading to a greater time horizon, prudence and self-efficacy rather than vice-versa. Moreover, the effects of assets on time horizon, self-efficacy and prudence were far stronger than that seen for income.

Assets have also been found to be associated with being self-directed, intellectually flexible, and future oriented (Kohn, Naoi, Schoenbach, Schooler, & Slomczynski, 1990), and with life satisfaction (W. Rohe & Stegman, 1994). The effect of assets on future orientation was also noted among participants of the American Dream Demonstration. In a sample survey of Individual Development Account (IDA) participants, 93 percent reported that they were more confident about their future because they had savings, 85 percent agreed that they felt more in control of their lives as a result of their IDAs, and 84 percent said they felt more secure economically. In addition, 60 percent of the sample reported that they were more likely to make future educational plans for themselves and their children, and for their retirement (McBride et al., 2003b).

Social Effects of Assets

Assets also yield a number of social effects, among which are the improvement of household stability and the enhancement of the well-being of offspring. More specifically, the accumulation of assets will improve family stability as assets cushion income shocks that occur with major illness or job losses, and thereby buffer the family from the cluster of psychological and social problems that could lead to marital disruption, depression, abuse and so forth (Sherraden, 1991). Studies on marriages have so far supported the proposed effects of assets on marital stability. Married couples who possess property and other financial assets have been found less likely to divorce than couples without assets (Page-Adams & Scanlon, 2001). Hampton (1982), in analyzing 575 married couples with data drawn from the Panel Survey of Income Dynamics (PSID), found that ownership of property and financial assets were negatively associated with marital disruption for African-American couples. The effect of assets on marital stability in couples has also been found to remain strong even when controlling for income (Galligan & Bahr, 1978), and for other social and economic factors (South & Spitzw, 1986).

Assets and Children's Outcomes

Assets may enhance the welfare of offspring as it provides an intergenerational connection that income and consumption cannot provide. Children from families with more financial assets tend to have better outcomes than children from families with fewer economic resources. Studies have found positive associations of assets with better child outcomes. In a review of literature, Rohe and his colleagues conclude that assets have positive associations with expanded opportunity sets for the children (W. M. Rohe, Van Zandt, & McCarthy, 2002). Assets have been associated with better child outcomes with respect to cognitive development, physical health, and socio-emotional behavior (Williams, 2003); better educational outcomes (Essen, Fogelman, & Head, 1978; M. S. Hill & Duncan, 1987); increased parental expectations for their children's education (Zhan, 2006); increased sense of economic security among youths (Scanlon & Page-Adams, 2006); higher self-esteem among adolescents (Whitebeck et al., 1991); lower rates on teen pregnancy and having children out of wedlock (Boyle, 2002; Green & White, 1997; Haurin, Parcel, & Haurin, 2002); lower risk of school drop-out (Green & White, 1997); and reduced vulnerability to poverty (Cheng, 1995). Assets have also been associated with better labor market outcomes, and fewer and shorter spells of unemployment as adults (Goss & Phillips, 1997).

III Assets and Children's Educational Outcomes: An Empirical Review

"Specifically, assets … stimulate development of human and other capital; … and enhance the welfare, well-being and life chances of offspring" (Sherraden, 1991).

Education has long been viewed as the primary key to socio-economic success (Haveman et al., 1998) and an important pathway to social mobility (Morgan & Kim, 2006). In our society today, the economic returns of schooling are rising (Mare, 1995), and success in school is increasingly valued and viewed as a primary determinant of adult independence (Taylor et al., 2004) and as an important channel to socioeconomic success (Goyette & Xie, 1999). A child's educational achievement or human capital development is therefore recognized as being one of the most important predictors of his or her future economic well-being and social mobility (Haveman & Wolfe, 1994; Keeley, 2007).

Assets theorists assert that assets play an important role in influencing children's educational outcomes (Boehm & Schlottmann, 1999; Conley, 2001; Sherraden, 1991), and that the effects of assets are independent of the effects of income and parents' education. In addition to the direct financial considerations such as paying for post-secondary education, family wealth also indicates the availability of economic resources to provide extra-curricular advantages such as the purchase of computers, tutoring and other enrichment opportunities. Family wealth is also a proxy for better housing in neighborhoods, better school districts, and better access to services (Oliver & Shapiro, 1995), factors which have also been found to positively impact on children's education. Assets have additionally been postulated to improve positive attitudes and behaviors, enhance future orientation, and help people make specific plans about their work and family (Yadama & Sherraden, 1996; Zhan, 2006). This may in turn positively affect parenting behaviors and investments, such as increasing the level of parental involvement and expectations, and thus affect children's educational attainment (Zhan, 2006).

Independent Effects of Assets

There is a growing body of empirical work that supports the postulations of the assets theorists. Several studies have examined the possible effects of assets on children's education, independent and distinct from income. Among the educational outcomes that have been studied are, inter alia, children's math and reading scores, number of years of education, school dropout, odds of graduating from high school, transitions into college, and college graduation. Mayer (1997b) for example, found that income from investments and inheritance explained more variance in children's educational test scores and achievement than did total family income. In fact, she concluded that the effects of income may be weaker and more modest than had been previously thought (Mayer, 1997a). Using data from the Panel Study of Income Dynamics (PSID), Hill and Duncan (1987) found that the first dollar from asset income has a significant effect on the years of education completed by both sons and daughters. However, no significant effects were observed for the first dollar from parents' labor, welfare, and all other sources of income.

Analyzing data of 591 children from female-headed households drawn from the National Survey of Families and Households (NSFH) 1987-88 dataset, Zhan and Sherraden (2003) also found in their regression analyses containing both income and assets that household total income had no significant effects on a child's academic performance or on children's high school graduation. Rather, controlling for a host of parents', household, and respondent characteristics including income and maternal education, they found children's academic performance to be significantly associated with assets in the form of homeownership. In addition, high school graduation is significantly associated with both homeownership and having savings of $3,000 or above (Zhan & Sherraden, 2003).

Conley (2001), using data on 1,126 children from the PSID, found that family permanent income, controlling for other respondent and parental characteristics, significantly predicted the total years of schooling, but not any of the post-secondary educational transitions. When the family's net worth was added to the model, permanent income no longer remained significant. Instead, family net worth is found to have significant effects on the total number of years of schooling, post-high school years of schooling, as well as transitions into college. Doubling of parental assets is associated with increasing the total number of years of schooling by 0.12 years, and an increase in post-high school years of education by 0.11 years. Doubling of assets also increases the probability of going to college after graduating from high school by 8.3 percent, and increase the chances of college graduated by 5.6 percent once enrolled (Conley, 2001). Nam and Huang (2008), using data from the PSID to examine the changing role of parental economic resources between the 1984 and 1994 cohorts, find that income is not associated with high school graduation of 15-17 year olds for both cohorts. However, they found that networth, controlling for income, was significantly associated with high school graduation and college enrollment for the 1984 cohort, while significant associations were found between liquid assets and both high school graduation and college enrollment for the 1994 cohort.

A large body of research finds positive associations of assets in the form of homeownership with children's educational outcomes. As a whole, the existing evidence suggests that homeownership has a positive impact on the children, even after corrections for omitted variables and sample selection biases (Dietz & Haurin, 2003). Essen and his companions, in studying the effect of housing tenure status on British 16-year-olds found that children of homeowners achieved significantly higher scores on math and reading tests than children of rented households (Essen et al., 1978). Boehm and Schlottman (1999), using data from the Panel Study of Income Dynamics, also found a positive association between homeownership and the educational outcomes of children from homeowning households, after controlling for a large number of household influences. Aaronson (2000), using data from PSID, found that homeownership retains a direct and positive association on high school graduation rates, apart from the indirect effect of residential stability through homeownership. Nam and Huang (2008) similarly found homeownership to be associated with college enrolment using PSID data. However, they did not find significant associations between homeownership and high school graduation, and further found that homeownership was negatively associated with college graduation for those who were 15-17 years old in 1994.

Asset ownership has also been found to predict school attendance among 13 to 18 year old children in Uganda. Analyzing a sample of 9,042 children drawn from the Uganda National household Survey 1999-2000, Ssewamala & Curley (2005) found that asset ownership is associated with increased likelihood of a child attending and staying in school, above and beyond socioeconomic characteristics such as parents' education and family income. In fact, income was no longer significant once assets were added to the regression model (Ssewamala & Curley, 2005). Green and White (1997) similarly found that asset ownership predicted children staying in school. Using data drawn from the Panel Study of Income Dynamics (PSID), the Public Use Microsample of the 1980 Census of Population and Housing (PUMS) and the High School and Beyond (HSB) datasets, Green and White conclude that the findings from the analyses of all three datasets consistently support the hypothesis that assets in the form of homeownership is a statistically significant and economically important determinant of whether children stay in school, even when controlling for a large number of other factors such as income and parents education. In addition, they found that the effect is strongest for children of low-income households (Green & White, 1997).

Mediating pathways

In addition to the direct effects of assets, the effects of assets on children's educational outcomes may also be mediated by a variety of factors. Research in the mediating pathways of asset effects however are still in the nascent stages, and the knowledge base in this area is still being developed. It is hypothesized that a possible pathway for the impact of assets is through increasing a person's future orientation, and that in turn brings about the other attitudinal and behavioral changes that are associated with having assets (Shobe & Page-Adams, 2001). Among the attitudinal and behavioral changes in relation to children's educational outcomes that have been investigated is that of parental expectations for their children's educational attainment. As reviewed earlier, parental expectations have been found empirically to be a significant determinant of children's educational achievement. Zhan and Sherraden (2003) tested the hypothesis that assets have a significant effect on mothers' educational expectations for their children among female-headed households. In their study of 591 children drawn from the National Survey of Families and Households (NSFH) 1987-88 dataset, they found that mothers who own a home have higher expectations than those who are not homeowners, controlling for maternal age, race, employment status, education, family structure, and child characteristics. In addition, mothers with savings of $3,000 or more have higher expectations than those without a savings account. Furthermore, household income is found to have no significant effects on mothers' educational expectation for their children in the study. They also found that when mothers' educational expectation is added to their regression models, children's academic performance is significantly associated with mothers' expectations and home ownership albeit with a smaller coefficient, and high school graduation is significantly associated with mothers' expectations and having savings of $3,000 or more. Household income remains non-significant in the analyses, and mothers' education becomes non-significant in the models as well (Zhan & Sherraden, 2003). Zhan and Sherraden (2003) hence conclude that there is tentative support that assets are positively associated with children's educational achievement, and that this relationship is partially mediated by mothers' educational expectations for their children.

Zhan (2006) further explored the relationship between assets, parental expectations and involvement, and children's educational performance using data from the mother-child data set of the National Longitudinal Survey of Youth (NLSY79). In this study of 1370 children between the ages of 5 and 12 in 1998 who resided with their mothers in the survey year of both 1998 and 2000, Zhan ran a series of regression models to test the effects of parental net worth, household income, mothers' expectations and parental involvement at school on children's performance in math and reading, controlling for mothers' age, race, marital status, family structure, mothers' work hours, and children's age and gender. She found the models explained more than 50 percent of the variation in children's math and reading scores, and that after controlling for income, mothers' education and other variables, the associations between parental net worth and children's academic performance in math and reading were positive and statistically significant. She further concluded that net worth had a stronger impact than income on children's education. In addition, she found that assets were also positively associated with mothers' expectations, and that about one-third of the relationship between parental assets and children's education could be accounted for by mothers' educational expectations for their children (Zhan, 2006).

The quality of the home environment in enriching the experiences of children as they are growing up have also been suggested as a possible factor mediating the effects of assets on children's educational outcomes. Orr (2003), for example, finds that the greater the exposure to cultural capital a child has in the home environment, the greater the child's math achievement. Using data from the NLSY79 and NLSY79-CYA, she also finds wealth to be significantly associated with cultural capital, and that cultural capital mediates the relationship between assets and children's math achievement. Cultural capital is measured by items such as going on outings with parents at least monthly, visiting at least one museum in the past year, being taken to performances at least once in the past year, having access to a musical instrument at home, and the child receiving special lessons or activities. Campbell (2007), also using data from the combined NLSY79 and NLSY79-CYA datasets, further finds that the effect of assets on children's PIAT math scores operates mainly through the home environment, with children from wealthier families having more supportive home environments and higher math achievement. In fact, when the home environment was factored into her regression models, the relationship between assets and math achievement becomes non-significant.

The effects of assets on children's educational outcomes may also operate through influencing children's own educational aspirations. Analyzing data from the Panel Study of Income Dynamics (PSID), Elloitt (2009) finds that children who have college savings accounts are nearly twice as likely to expect to attend college as those without a savings account. In addition, children with these savings accounts also perform better in school, with 4.57 points higher in math scores. In addition, he finds that children's expectations partially mediate the effects of having college savings accounts and math achievement. Destin and Oyserman (2009), in an experiment manipulating mind-sets about college among low-income adolescents as being either "open" (financially attainable), "closed" (expensive), or no-prime (control), find that children from the open condition expected higher grades and planned to spend more time on homework than those assigned to the closed or no-prime groups. They suggest that assets linked to goals create an open-path mindset that maintains aspirations and effort, leading to eventual realization of the goal of college graduation.

While the empirical studies reviewed lend support to the asset theory that assets lead to better educational outcomes for children, the conclusions have to be interpreted with caution. Among the critiques of the empirical studies is whether assets have been appropriately conceptualized. There are three major perspectives through which assets are conceived and measured (Nam, Huang, & Sherraden, 2006). In the consumption model, assets are defined as a storehouse for future consumption; and in the social stratification theory, assets are viewed as an indicator of class status and as a major vehicle for the intergenerational transmission of class and privilege. Finally, in the assets for development perspective, assets are conceived as vehicles for socioeconomic development (Nam et al., 2006). Here, assets are defined broadly by Sherraden (1991) as “stocks of wealth” (p. 96) that comprise “capital for investment which in turn, generates future flows of income” (p.100). In the studies reviewed, assets are mainly conceptualized in terms of consumption. However, the assets theory conceptualizes assets as stocks of wealth that could be leveraged for development. Conceptualizing assets through the lens of a different perspective may lead to incorrect conclusions.

Measurement of assets is another concern in the review of the empirical work. Adequate measures, regardless of whether they are scale instruments or indices, are essential in theory building. Without valid and reliable measures, even the most eloquent of theories cannot be tested, and plausible alternative theories cannot be refuted (Blalock, 1968). In addition, accurate theories may be evaluated as false due to aspects of poor measurement (Gillespie, 2000), or conversely evaluated as true based on suspect measures. To validate the theoretical propositions of the assets for development perspective, it is imperative that valid and reliable measures of assets be established, agreed upon, and consistently used across studies. In the studies reviewed, the asset measures used differ from study to study, ranging from assessing the value of net worth, financial assets, liquid assets, to ownership of specific asset types such as homes, among others. In fact, there is a lack of consensus on the definition and measurement of assets.

Sherraden (1991) himself acknowledges as much when he noted that there are more than a dozen synonyms for the word *assets*, and that the word embraces distinct social and psychological content, in addition to the oft familiar accounting concept. To Sherraden, “there is no single correct definition of assets” (p. 106). Rather, it is the particular context in which assets is to be used that will dictate the appropriateness of its definition.

The studies are also generally silent on the mechanisms of the asset effects. We do not yet know, for example, what it is about owning a house that leads to better school attendance, school performance, and educational attainment in children. Is it homeownership that matters, or is it some other unmeasured factor that leads to both homeownership and better educational outcomes? Studies that did include possible mediating pathways measured the mediators at the same time as when the outcomes are measured (e.g. Orr, 2003; Zhan, 2006). The temporal requirement for causality is therefore not satisfied. In other words, while the state of the art for the asset perspective allows us to conclude that assets covary with various mediators and educational outcomes, we are not quite able to conclude that assets lead to either of these.

IV Research Aims and Methods

Research Aims

The main theory framing the study is Sherraden's asset-based welfare theory that proposes that the assets will lead to positive social, psychological and economic effects. The focus of this study is on children's educational outcomes. In addition, it will build on Paxton's (2001) classification of the asset experience to unpack whether the asset effect operates through the process of asset accumulation, through the possession of assets, or both.

Sherraden's (1991) theory of welfare based on assets has been around for almost two decades now. However, much of the work that has been done over the years has focused more on technical matters rather than on the broader development of theory (Midgley, 2003). Several theoretical areas remain under-clarified. While the theory proposes that assets lead to various positive outcomes, it does not specify if and when the different asset experiences, asset types, and amount of assets matter. Neither does it identify the mechanisms through which the asset effects occur. Little empirical work has been carried out to test existing or develop new theoretical propositions on the possible mechanisms by which assets lead to the asset effects (Scanlon & Page-Adams, 2001;

Zhan, 2006). More empirical and theoretical work is needed to better understand and specify why and how the various dimensions of the asset experience lead to the asset effect as it has important policy and practice implications.

Wealth is increasingly a topic of interest to the public, policy makers and researchers, especially since the inclusion of wealth data in nationally representative datasets over the last two decades. The recent availability of longitudinal wealth data in surveys such as the NLSY79 and PSID further spurred interest among researchers on the predictors, covariates and effects of wealth accumulation over time. However, this line of inquiry is still in its nascent stages. Much of existing wealth research has focused on either the very rich or the elderly, and most utilized cross-sectional data, or pooled longitudinal data. Relatively little is known about the wealth accumulation process for young adults and beginning families (Zagorsky, 1999), especially about asset growth trajectories for these families.

The majority of the studies also make the assumption that the entire sample under investigation shares a single growth trajectory. However, it is reasonable to believe that this is not the case, and that there is more than one growth trajectory for wealth accumulation. Sherraden (1991) suggests that when the poor are provided with some initial amount of assets, and the opportunities to accumulate assets, they will be on a different asset accumulation trajectory from those who are only on income support. They will have the ability to accumulate even more assets in the future. In other words, there may be at least two different trajectories for wealth accumulation – a relatively flat trajectory for the poor who have only income support from the government, and an increasing trajectory for those provided with some initial assets.

The first research aim of this study is to examine if there is, in fact, more than one growth trajectory for families over time. It is hypothesized that the asset accumulation experience will be different for different people, as such, two or more asset trajectory classes can be derived and identified from the data. The study tracks the net worth of young families with children born in 1986 or 1987 over 13 years, from 1987 when the mothers were between the ages of 23 to 30, to the year 2000 when mothers were between the ages of 36 to 43.Trajectories over two time periods are estimated – the first over the early childhood years from around birth to ages six or seven, to test the relationship between the asset trajectories and children's outcomes at around the third grade in elementary school, and the second over the early to middle childhood years, from around the birth of the child to ages 13 or 14, to test the effects of different asset trajectories on high school graduation rates by the time these children turned 19 or 20 in the year 2006.

There are also empirical indications that the effects of assets may be different based on the family's socioeconomic (SES) background. Loke and Kim (2008), for example, noted that the different asset measures of net worth, financial assets and liquid assets have differential effects on children's math scores based on the family's income group. Again, the current state of knowledge does not allow us to address if indeed there are differential effects based on the socioeconomic background of the individual, be it income, net worth, or some other measure of SES. There is also no information available on whether the different asset accumulation trajectories are associated with different educational outcomes for children. Building on the first research aim, the second research aim of the study is to investigate the effects of different asset accumulation trajectories on educational outcomes. Assets, and asset accumulation trajectories in particular, are reasonable indicators of a household's socioeconomic status as they reflect the accumulation of resources over time, in addition to current financial holdings. It is hypothesized that children from households with lower asset holdings around the time of birth, and whose asset levels remain relatively stable, will have poorer educational outcomes compared to children from households with increasing asset trajectories, or with higher initial levels of asset holdings around the time of birth.

Sherraden (1991) also posits that the accumulation of assets changes the way people think and behave, and that the world responses to them differently as well. Earlier studies suggested that assets can lead to higher levels of parental expectations (Zhan, 2006; Zhan & Sherraden, 2003), children's own educational aspirations (Destin & Oyserman, 2009; Elliott, 2009), and the level of conduciveness and supportiveness of the home environment to learning (L. A. Campbell, 2007; Orr, 2003), and that the effects of assets are mediated by these factors as well. Presently, little is known about whether the mediating pathways are the same across the different asset trajectory classes. It is hypothesized that parental expectations, children's educational aspirations, and the quality of the home environment will similarly mediate the effects of the asset on children's educational outcomes across the different asset trajectory classes. In addition, it is hypothesized that children from households with lower levels of initial assets and with slower rates of growth will have lower levels of parental expectations, children's educational aspirations, and quality of home environment towards learning (research aim three).

There is also the theoretical question of whether the timing of asset holding, and timing of the asset-poverty episodes, matters. According to the life span development approach, development occurs over the life course of an individual, and that events that impinge on a person has differential effects depending on when during the life course the event occurs, and the nature of the interactions subsequent to the event that either reinforces or offsets the effect of the event on the person's development (Haveman & Wolfe, 1995). Research has found that economic deprivation in the early years of a child life has negative effects on the child's cognitive development (Duncan, Brooks-Gunn, & Klebanov, 1994), and that being on welfare in the young childhood years has more of an effect on educational attainment than does welfare receipt in the teenage years (Baydar, Brooks-Gunn, & Furstenberg, 1993). These studies also indicate that the negative effects of poverty are greatest during the formative years of one's childhood. Conversely, the interventions can be most effective when given during the pre-school years (F. A. Campbell, Pungello, Miller-Johnson, Burchinal, & Ramey, 2001). It is conceivable that there may be parallels with regard to the timing of the episodes of asset-poverty and asset accumulation. It could well be that there are certain critical time periods in one's childhood that the possession and accumulation of assets may have the largest impact. Conversely, the absence of assets during certain time periods may also have significantly detrimental effects. However, little is known about the timing of the asset experience and its effects on the life chances of children. Should asset-building for children begin at or near birth, or should it wait till some later stage in the life course? Will children from households who experience asset accumulation during early childhood have better outcomes than those who experience accumulation only from middle childhood onwards? This is the fourth and final research aim that this study will address. It is hypothesized that children who experienced asset accumulation during early childhood will have better outcomes than those who experience it later in middle childhood.

In summary, the research aims are:

1. What are the asset accumulation trajectories for households with children?
2. What are the effects of different asset accumulation trajectories on children's educational outcomes?
3. What are the pathways mediating the effects of asset accumulation trajectories on children's educational outcomes?
4. Does the timing of asset accumulation matter?

Data and Sample

Data from the National Longitudinal Survey of Youth (NLSY79) and the associated NLSY79 Child and Young Adult (NLSY79-CYA) was used for this study. The NLSY79 is a nationally representative sample of 12,686 youths in the United States who were 14 to 21 years old when they were first interviewed in 1979. Sponsored by the Department of Labor, this national probability sample included an overrepresentation of blacks, Hispanics or Latinos, and economically disadvantaged non-black/non-Hispanics. The NLSY79 contains extensive information about employment, education, income, assets, training and family experiences of respondents. Data on these respondents have been collected yearly from 1979 to 1994, and biennially from 1996 to the present, providing researchers the opportunity to study in great detail the experiences of large group of adults who can be considered representative of all American men and women born in the late 1950s and early 1960s and living in the U.S. in 1979 (Center for Human Resource Research, 2008). As of the 2006 interview round, respondents had attained the ages of 41 to 48 years.

Biennially since 1986, children born to females in the NLSY79 sample have been surveyed. Known as the NLSY79 Child and Young Adult (NLSY79-CYA), a battery of child cognitive, socio-emotional, and physiological assessments are administered to NLSY79 mothers and their children during the biennial surveys. The original NLSY79 main youth sample included 6283 women in 1979, including 456 women who were in the military and another 901 economically disadvantaged white oversample, who were subsequently dropped from the survey due to budget constraints (Center for Human Resource Research, 1998). The sampling weights for younger children and young adults adjust the unweighted data for sample attrition of mothers and their children since the first survey round (1979) and the sample reduction due to the loss of the military and economically disadvantaged white oversample and adjust the sample for the over-representation of black and Hispanic youth. With appropriate weights, the children of NLSY79-CYA may be considered a representative sample of children who have been born to this national sample of NLSY79 women (Center for Human Resource Research, 2006).

The NLSY79 and NLSY79-CYA datasets are well suited for the purposes of this study for several reasons. First, the NLSY79 dataset contains detailed longitudinal information on assets that have been collected at relatively short regular intervals, and over a long period of time. Very few national representative datasets contain information on assets (Ratcliffe et al., 2007), and the only other survey that follows the same individual longitudinal over an extended period of time is the Panel Survey of Income Dynamics (PSID). The PSID, however, collects asset and liability data every five years between 1984 and 1999. The NLSY79, on the other hand, collects asset and liability information yearly from 1985 to 1994, and biennially since 1994, with the exception of 1991, 2004 and 2006 where budgetary constraints eliminated questions on wealth in those survey years (Center for Human Resource Research, 2008).

Second, the NLSY79-CYA provides data rich information on the children of women of the NLSY79 sample biennially from 1986 onwards. This allows us to follow a particular cohort of children born in 1986 or 1987 from birth to 2006 when they are ages 19 or 20. In addition to information on the cognitive and educational outcomes of these children, information on the quality of the home environment of the children as they are growing up is also available. The PSID, in comparison, has only two waves of child outcomes data available, in 1997 for children between the ages of 0 and 12, and in 2003 when the children are between the ages of 5 and 18.

The quality of the data on wealth in the NLSY79 has also been evaluated to be comparable to other major surveys assessing wealth, such as the Survey of Consumer Finances, the Panel Study of Income Dynamics, and the Survey of Income and Program Participation (Engelhardt, 1998; Zagorsky, 1997). In addition, the NLSY79 maintains extremely high participation rates, with response rates of between 83.2 percent and 92.5 percent from 1988 and 2000 (Center for Human Resource Research, 2008). In addition, after 17 rounds of interviewing, 72.1 percent of respondents answered the survey every single round (Zagorsky, 1999).

The final sample consists of 1036 children from 991 households. These children were all born in either 1986 or 1987, and are followed from around the time of birth to the year 2006, when they were ages 19 or 20. Household net worth, on the other hand, is tracked from 1987 to 2000. To adjust for the non-independence of observations for children belonging to the same household, the children were clustered by their mother's unique identifier. Custom weights for children who were surveyed in 1996, 2004 or 2006, generated online at the National Longitudinal Surveys' website (http://www.nlsinfo.org/web-investigator/custom_weights.php) were also used. A total of 95 children were assigned weights of zero as they were not surveyed in all of the years listed. A comparison of means revealed that children with zero weights are not statistically different from children with non-zero weights with respect to key socio-economic indicators.

Measures

Asset Measures

The research literature suggests that different types of assets may be associated with different asset effects. For example, Nam & Huang (2008) finds differential effects of homeownership and liquid assets on educational attainment. Bynner (2001) also finds that assets gained from inheritance had no significant associations with subsequent labor market participation whereas assets in the form of investments are. Current asset-building policies for children focus mainly on increasing money or financial resources to use as young adults. Nevertheless, this study adopts net worth as the asset measure as it is the most commonly used construct in earlier studies.

In spring of 2008, a revised set of NLSY79 assets was released to the public, including the constructed total net worth (imputed) variable, which is used for this study. This variable is operationalized as a continuous variable that sums the value of the asset types net of the total liabilities. There are 15 asset and debt measures in each round of data collection of NLSY79. The asset items are values of home, cash saving, stocks/bonds, trusts, business assets, car, other possessions, IRAs, 401Ks and CDs. The debt items are mortgages, other property debt, business debt, car debt and other debt.

As part of the data-cleaning process undertaken by the Center for Human Resource Research, the data managers of the datasets, implausible outliers were removed from the dataset and missing values imputed. A consistent top-coding algorithm was also applied across the different survey years to protect the identity of the wealthiest top 2 percent, with their net worth replaced by the mean value of the top two percentile (J. Zagorsky, personal communication. July 16, 2008). For the purposes of this study, in the nine instances where net worth were top coded, values for the net worth variable were first recoded as missing, and then re-imputed through a multiple-imputation process detailed in the subsection on missing data below.

The total net worth data was tracked at the household level from 1987 to 2000, scaled to 10,000's, and adjusted for inflation to 2000 dollars using the Consumer Price Index (CPI) calculator available at the Bureau of Labor Statistic's website at http://www.bls.gov/data/inflation_calculator.htm.

Child Educational Measures

PIAT. The Peabody Individual Achievement Test (PIAT) Math, Reading Recognition and Reading Comprehension subtests that are administered to children ages five or older were used as one of the outcome measures. The three subtests are among the most widely used brief assessment of academic achievement, and has demonstrably high test-retest reliability and concurrent validity (Center for Human Resource Research, 2006). The PIAT was standardized on 2,887 children in kindergarten through 12th grade in the late 1960s. Completion rates ranged from 89 percent for Latin American children to 94 percent for European American and African American children. The one-month test-retest reliability was estimated at 0.74 for the math subtest, and 0.89 for reading sub-test (Bradley & Corwyn, 2003).

The PIAT Math subtest offers a wide-range measure of achievement in mathematics for children. This subscale consists of 84 multiple-choice items of increasing difficulty that measure a child's attainment in mathematics as taught in mainstream education. It begins with such early skills such as recognizing numerals and progresses to measuring advanced concepts such as geometry and trigonometry.

The PIAT Reading Recognition and Reading Comprehension subtests assess the attained reading knowledge and comprehension of children. The PIAT Reading

Recognition subtest measures word recognition and pronunciation abilities. It consists of 84 multiple-choice items with increasing difficulty from preschool to high school levels. The skills assessed in this subtest include matching letters, naming names, and reading single words aloud. Comprised of 66 multiple-choice items with increasing difficulty, the PIAT Reading Comprehension subtest measures a child's ability to derive meaning from sentences that are read silently (Center for Human Resource Research, 2006).

The standardized PIAT scores measured in 1996, when the children were ages 9 or 10, were used in this study. The standardized scores have a mean of 100, and a standard deviation of 15. Scores from the PIAT Math, Reading Recognition and Reading Comprehension subtests were constructed as separate continuous variables. In addition, as the PIAT subtests are designed to measure the underlying academic achievement of children (Center for Psychological Studies, n.d.; Klinge, Harper, & Vaziri, 1974), a single continuous latent PIAT variable was also constructed and used in this study.

High School Graduation. Whether or not the child graduated from High School by 2006, when the child is 19 or 20 years old, is the other outcome variable. This variable is constructed as a dichotomous variable, with 1 indicating that the child has graduated from High School or has a GED equivalent.

Socio-economic Measures

Total Net Family Income. The constructed total net family income summary variable in the NLSY79 dataset is a sum of all income received by the respondent and spouse for the survey year. This continuous variable is top-coded in the NLSY79 dataset for confidentiality reasons, with value of the highest two percent of income earners recoded as the mean of the top two percentile. For this study, the top-coded values are first recoded as missing, and subsequently replaced with an imputed value using the MICE process. Data for each survey year from 1987 to 2000 is used, scaled to 10,000s, and adjusted for inflation to year 2000 dollar values using the Consumer Price Index (CPI) calculator available at the Bureau of Labor Statistic's website at http://www.bls.gov/data/inflation_calculator.htm. As the data has acceptable skewness values, the data is not transformed.

Mother's Marital Status. This variable is operationalized as a dichotomous variable, with 1 indicating that the child's mother is married and living with her spouse in a particular survey year.

Mother's Employment Status. Constructed as a dichotomous variable, this variable indicates whether the child's mother is employed at least part-time, or in active military duty, in the survey year.

Mother's Age. This continuous measure indicates the age of the child's mother in 1986.

Mother's Race. Mother's race was initially dummy-coded to African American, Hispanic, and non-Hispanic/non-black. However, due to issues of singularity in the analysis models, mother's race was operationalized as a dichotomous variable, with 1 indicating that the mother is non-Hispanic/non-black.

Parent's Educational Attainment. This variable measures the human capital that is available in the family, and data collected at two time points, in 1993 and in 2000, are used in this study. In both years, the variable is constructed as a dichotomous variable, with 1 indicating that one or both of the child's parents have at least an Associate's degree by that particular time.

Number of Children in the Household. This continuous variable indicates the number of biological, step or adopted children in the household. Data collected in 1993 and 2000 are used in this study.

Child's gender. Constructed as a dichotomous variable, values of 1 indicate that the child is a male.

Psycho-Behavioral Measures

Home Cognitive Stimulation. The quality of cognitive stimulation in the home environment is one of two sub-scales of the short-form version of the HOME (Home Observation for Measurement of the Environment) Inventory developed by Caldwell and Bradley (1984) to measure the nature and quality of the child's home environment from birth to adolescence . The HOME-Short Form (HOME-SF) is divided into four parts: for children under age three; for children between the ages of three and five; for children ages six through nine, and lastly for children ten and over (Center for Human Resource Research, 1998). Although some questions are asked of children of all ages, a different series of questions is used depending on the age of the child, ranging from nine items for the cognitive stimulation sub-scale for children under three, to 13 or 14 items for older children (see Appendix 1). The total raw score for the HOME-SF, as well as the total scores for the cognitive stimulation and emotional support subscales, is a simple summation of the recorded individual item scores specific to each age group. The raw scores are also internally normed within the NLSY79 CYA sample to provide percentile and standardized scores. The standardized scores for the cognitive stimulation subscale were used for this study.

Mother's Expectations. Mother's expectations for her children's educational outcomes was measured by the question "how far mom thinks child will go in school", where 1 indicates leaving high school before graduation, to 5 indicating the child getting more than four years of college. The response option of “6 = something else” was recoded as missing and the value imputed for the purpose of this analysis. This variable measured in 1996 was used in the model.

Child’s Problem Behaviors. The Behavior Problems Index (BPI) was created to measure the frequency, range, and type of behavior problems for children age four and over (Peterson & Zill, 1986), and comprises 28 questions dealing with specific behaviors such as hyperactivity, anxiety, dependency, aggressiveness and peer conflict that children may have exhibited in the three months prior to the survey (see Appendix 2). It is among the most frequently used of the NLSY79 child assessments, with its validity and reliability clearly established (Center for Human Resource Research, 1998; Mott, Baker, Ball, Keck, & Lenhart, 1995). The alpha estimated at 0.89 for young children, and 0.91 for adolescents. Test-retest correlation, corrected using the Spearman-Brown formula, was estimated at 0.92 (Bradley & Corwyn, 2003). In the NLSY79 CYA dataset, three sets of scores are available for BPI – the raw scores, and the percentile and standard scores (with a national mean of 100 and a standard deviation of 15) that have been normed based on data from the 1981 National Health Interview Survey. For this study, the standardized BPI scores measured in 1996 will be used.

Child's Educational Aspirations. This variable was measured by the question "how far child thinks he/she will go in school. The response options for this self administered item range from "leave high school before graduation" (1) to "get more than 4 years of college "(5). The response option of "something else" (6) was recoded as missing and the value imputed for the purpose of this analysis. This item is only asked for children ages 10 and above, and hence was only included for the model analyzing the effects of assets on high school graduation.

Limitations on School Work. This dichotomous variable indicates whether the child has any physical, emotional, or mental condition that limits or prevents his or her ability to do regular school work. The variable is measured in 1996, with the value 1 indicating that the child has limitations on school work.

Missing Data

Missing data is handled using both the multiple imputation and the full information maximum likelihood (FIML) approaches. The R package MICE (Multivariate Imputation by Chained Equations) was used to generate 5 imputed datasets from the original data. This program uses a Gibbs sampler to produce random samples for each missing value, drawing from the multivariate distribution and taking into account all available information from other others in the model (Van Buuren & Oudshoorn, 2000). With the exception of the number of children in the household, all other variables had missing values imputed through this process. In FIML, the model is fitted to non-missing values for each observation, ignoring the presence of missing values. FIML estimation has the strengths of single or multiple imputation, and was found to yield similar estimates as multiple imputation in simulations studies (McCartney, Burchinal, & Bub, 2006).

Statistical Analysis

Structural equation modeling (SEM) techniques, including General Growth Mixture Modeling (GGMM), are adopted and implemented in Mplus. GGMM is an extension of Latent Growth Curve Modeling (LGC). LGC is a structural equation modeling approach in which individual growth curves are estimated from fixed paths in the measurement model (McCartney et al., 2006). These growth curves or trajectories describe intra-individual change over time by estimating two latent constructs in a structural equation model – the initial levels (the intercept), and the rate of change (the slope) (Wickrama, Lorenz, Conger, & Elder, 1997). The estimated paths in the SEM also describe direct and indirect associations among the latent variables, and between the latent variables and other covariates, and with other proximal or distal outcomes

(McCartney et al., 2006). The major advantages of the SEM approaches include their ability to test the mediation hypothesis as well as the ability to account for some correlated errors in predictors arising from repeated measurement (McCartney et al., 2006).

LGC models assume that all individuals are drawn from a single population with common population parameters, resulting in the estimation of a single mean sample growth curve. However, there may be subpopulations with different growth trajectories within the sample, and models assuming common growth parameters for the entire sample may be inaccurately specified. GGMM is an extension of LGC in that it relaxes the single population assumption to allow for parameter differences across identified subpopulations, whether unobserved or determined a priori. The assumption is that that the population under investigation consists of a mixture of distinct subgroups defined by their developmental trajectories (Li, Duncan, Duncan, & Acock, 2001). Different trajectories are estimated in GGMM for each underlying subpopulation, where individuals in the different classes can vary around different mean growth curves that are estimated for each subpopulation (Muthén, 2004). Robust Maximum Likelihood estimators are used in the analyses as they are able to handle violations of the normality assumptions.

Analytic Model and Approach for Research Aim 1

The first research aim is examining whether there is heterogeneity in asset accumulation patterns for households with young children. Following the work of prior researchers (e.g. Jung & Wickrama, 2008; Muthén, 2006; Wang & Bodner, 2007), unconditional 1-class latent growth curve models with linear and quadratic growth curves were first estimated to determine the shape of the growth patterns. The χ^2 goodness-of-fit statistic, together with various fit indexes such as the Bentler's Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), and the root mean square error of approximation (RMSEA,Steiger & Lind, 1980) were used for evaluating the models. Using guidelines suggested by Hu and Bentler (1999), cutoff values of close to .95 for TLI and CFI, and close to .06 for RMSEA are deemed as reflecting a reasonable model fit.

After the shape of the growth factors has been determined, the number of latent classes was determined by comparing unconditional models with increasing number of classes. For mixture modeling, the conventional chi-square-based fit indices such as the CFI, RMSEA, etc, are not available when the number of latent classes is more than one. While there is currently no common acceptance of the best criteria for determining the number of classes in mixture modeling (Nylund, Asparouhov, & Muthén, 2007), a number of approaches have been suggested and adopted by different researchers. Among the possible approaches is the use of likelihood ratio tests such as the Lo-Mendell-Rubin

(LMR) likelihood ratio test or the Adjusted Lo-Mendell-Rubin Likelihood Ratio Test (Adjusted LRT) which compares the K-1 class model to the K-class model. A significant test result indicates that the K-1 class model should be rejected in favor of the model with at least K classes (Lo, Mendell, & Rubin, 2001). Another approach would be to compare the information criteria, such as Akaike's information criterion (AIC, Akaike, 1974), Bayesian information criterion (BIC, Schwartz, 1978), and sample-size adjusted BIC, among growth mixture models with different number of classes. Models with smallest information criterion values are deemed to fit the data better. Entropy values, which indicate latent classification accuracy (Jedidi, Ramaswamy, & Desarbo, 1993), are also regularly used to identify the optimal number of latent classes for the data. Ranging from 0.00 to 1.00, higher values indicate better classification. Yet others have suggested that theory and interpretability of the data, in addition to the various tests and information criteria, should guide the determination of the optimal number of latent classes (Boscardin, Muthén, Francis, & Baker, 2008; Rindskopf, 2003).

Simulation studies comparing the different approaches further found that different methods or indices may be more appropriate in some situations than others. Muthén (2001; 2004), for example, states that BIC is preferable when within class variability in growth curves is permitted. Tofighi and Enders (2007), however, found that sample size adjusted BIC and the Lo-Mendell-Rubin (LMR) likelihood ratio test are more promising as candidates in determining the number of latent classes. Nylund, Asparouhov & Muthén (2007), on the other hand, concluded that BIC performs better than SABIC and the AIC, and that the bootstrap likelihood ratio test (BLRT), which is not available for complex models, outperforms the LMR. Heeding the advice of Wang and Bodner (2007) for researchers to pay attention to all these methods and indices as well as the context of the GMM when selecting the best unconditional growth-mixture model, I used AIC, BIC, SABIC, entropy, LMR and Adjusted LRT to inform the selection of the optimal number of latent classes for the growth mixture models. In addition, theory and the interpretability of the findings also guided the selection of the growth mixture models (Rindskopf, 2003).

To correctly specify the model, find the proper number of classes, and correctly estimate class proportions and class membership, it is essential that antecedents of class membership and growth factors be included in the GMM model (Muthén, 2004) as the next step after estimating the unconditional models (Muthén, 2006). Hence after determining the optimal number of classes with the unconditional model, both time-varying and time-invariant covariates were added, and the model re-estimated and evaluated to determine the best solution in terms of class structure, number of classes, and class membership. Time varying covariates are longitudinal measures with data collected at each survey wave. In other words, the values of these covariates vary with time. On the other hand, time-invariant covariates are variables in the model with values that do not vary over time. These variables are typically measured at the first or last wave of data collection. The time-invariant covariates included in the models are the age and race of mothers, the educational attainment of parents, and the number of children in the household. The time-varying covariates are total net family income, and mother's employment and marital status.

For research aim 1, which is to explore if there are different asset accumulation trajectories for households with children, models for different periods of the child's life-stage are estimated. The first model – the early childhood model – estimates the asset accumulation trajectories of households around the time of birth of the child in 1987 to when the age is around 6 years old in 1993 (Fig 1). In this model, the net worth indicators at each wave were regressed on the time-varying covariates of total net family income, mother's marital status and employment status, and are in turn, used to estimate the latent growth factors of the initial level of assets and the rate of change in assets. The asset trajectory classes were then estimated from the latent growth factors and the time-invariant covariates. Asset trajectory classes derived from this model are used subsequently to test the effects of different asset trajectories on children's educational outcomes at around third grade.

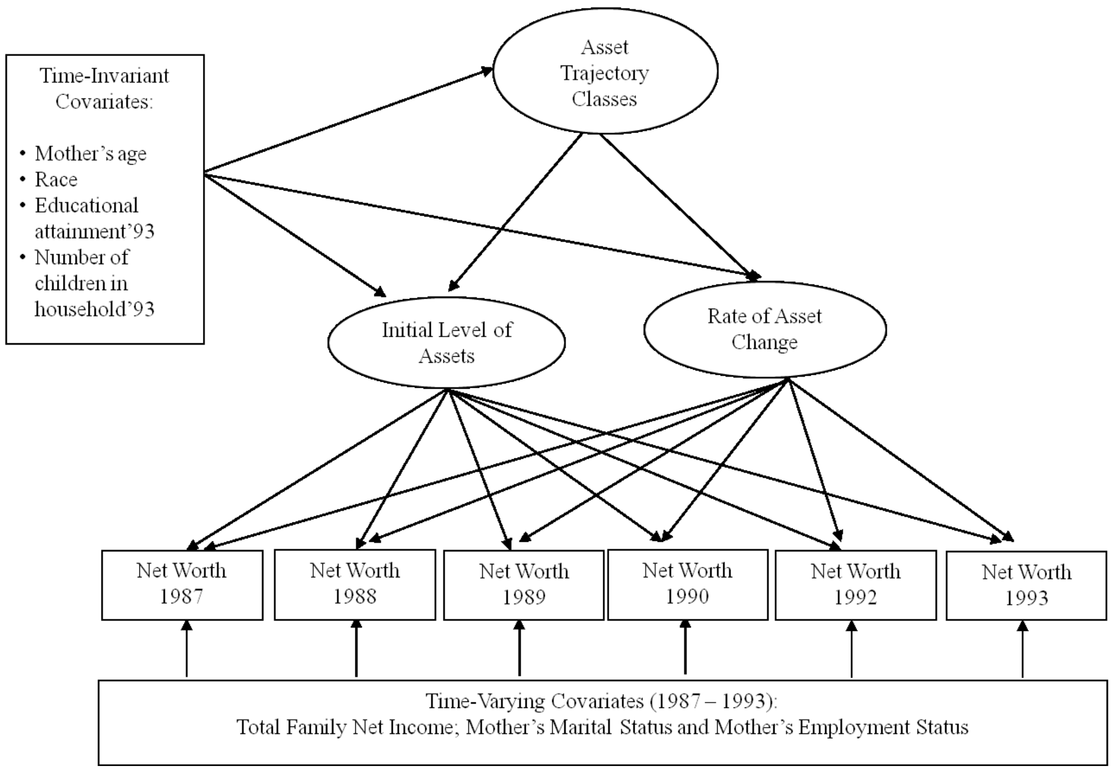

Figure 1. Growth Mixture Model for Early Childhood

The second model – the early-mid childhood model, estimates the asset accumulation trajectories of households from 1987 to 2000, from around the year of birth of the child to ages 13 or 14 (Fig 2). The asset trajectory classes estimated from this model are used subsequently to test the effects of different trajectory classes on children's high school graduation. Similar to the early childhood model, the net worth indicators were regressed on the time-varying covariates. Together with the time-invariant covariates, the net worth indicators then estimate the latent growth factors and subsequently the asset trajectory classes.

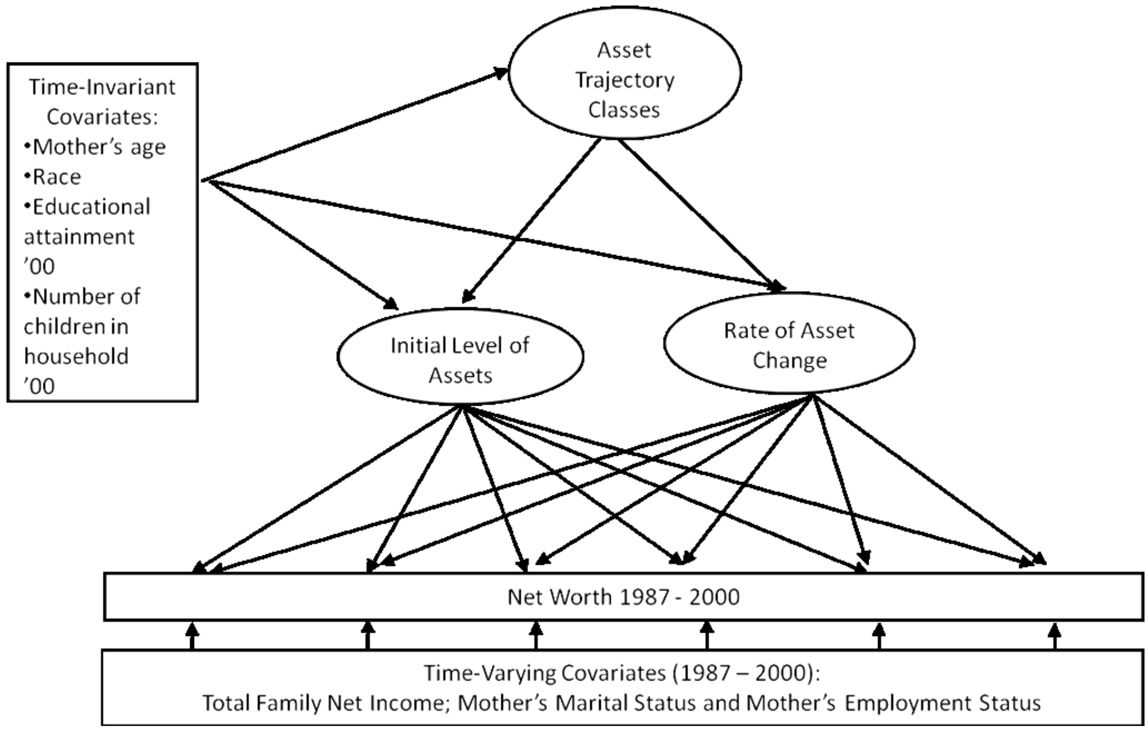

Figure 2. Growth Mixture Model for Early-Mid Childhood

Analytic Model and Approach for Research Aims 2 and 3

Separate structural equation models are estimated to test the effects of assets on PIAT scores (PIAT model) and on the odds of high school graduation (high school model). As one of the advantages of SEM is the ability to test mediation models, relevant mediators are included in the models. Model fit is evaluated using the guidelines set by Hu and Bentler (1999), or by evaluating AIC, BIC and SABIC values. Conceptually, the full SEM models are depicted in figure 3 for the PIAT model, and figure 4 for the high school model.

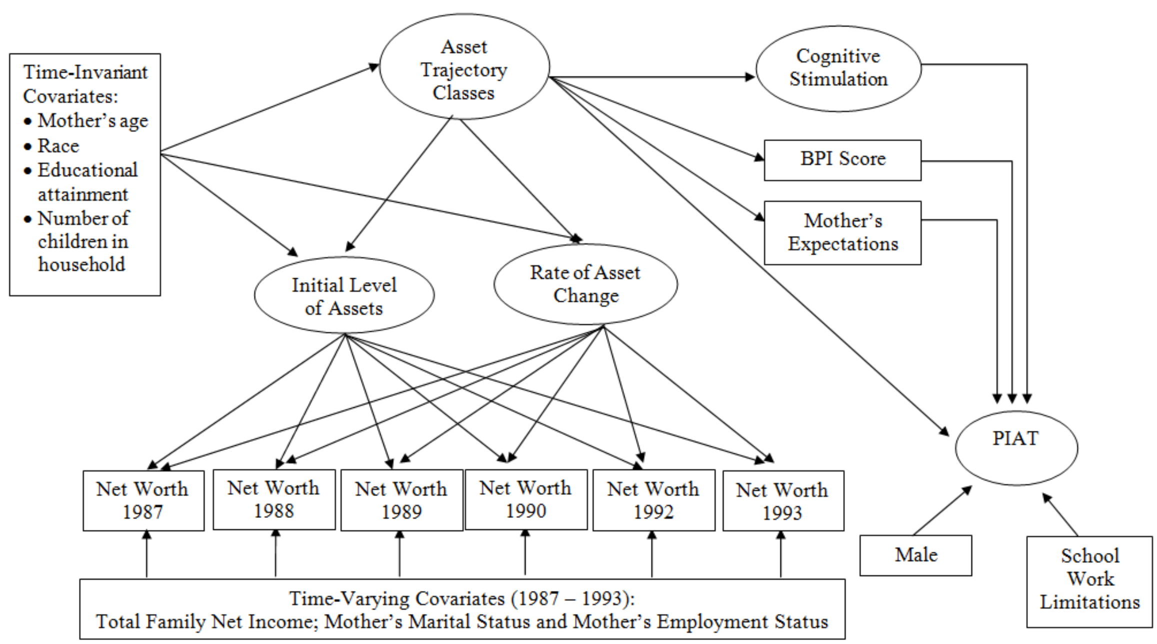

Figure 3. Mediated Pathways for the Effects of Asset Trajectories on PIAT Outcomes

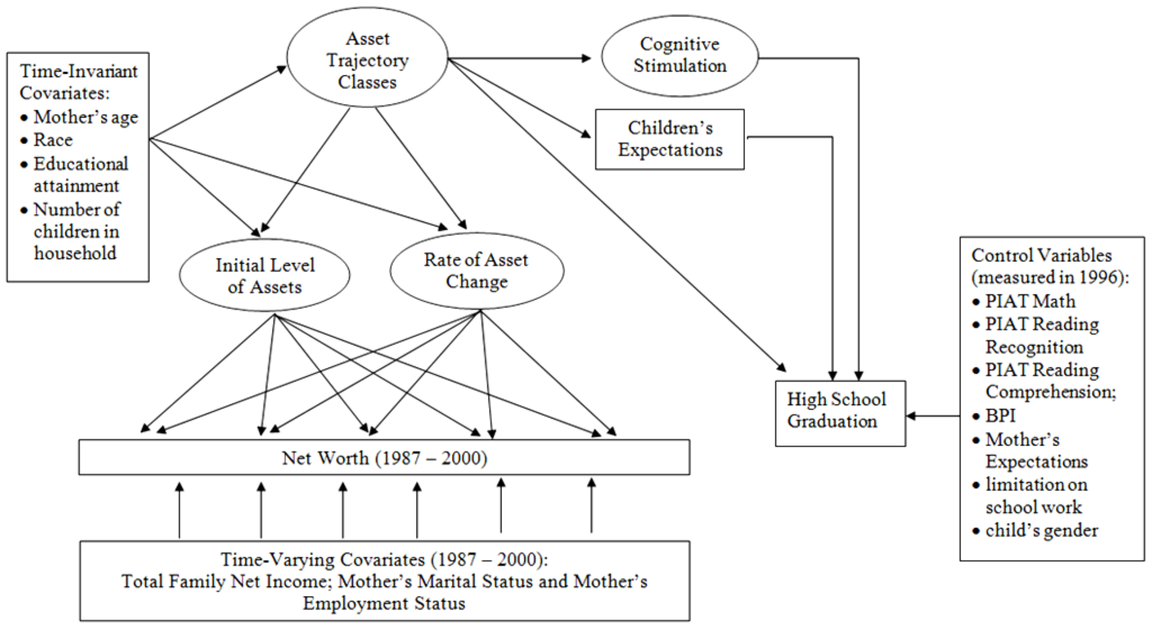

Figure 4. Mediated Pathways for the Effects of Asset Trajectories on the Odds of High School Graduation

For the PIAT Model, the asset trajectory class assignments are drawn from the early childhood GMM model in research aim 1. In this model, the latent PIAT variable is regressed on the asset trajectory classes as well as on the latent variable for the quality of cognitive stimulation in the home environment, children's standardized scores on the Behavioral Problem Index, and mother's expectations for their children's education. To test if home cognitive stimulation, mother's expectations and children's BPI scores mediate the relationship between assets and children's PIAT outcomes, these variables are also regressed on the asset trajectory classes. In addition, children's gender and whether the child has any limitations that may impede school work are included in the model as controls. The simplified analysis model is shown in figure 5.

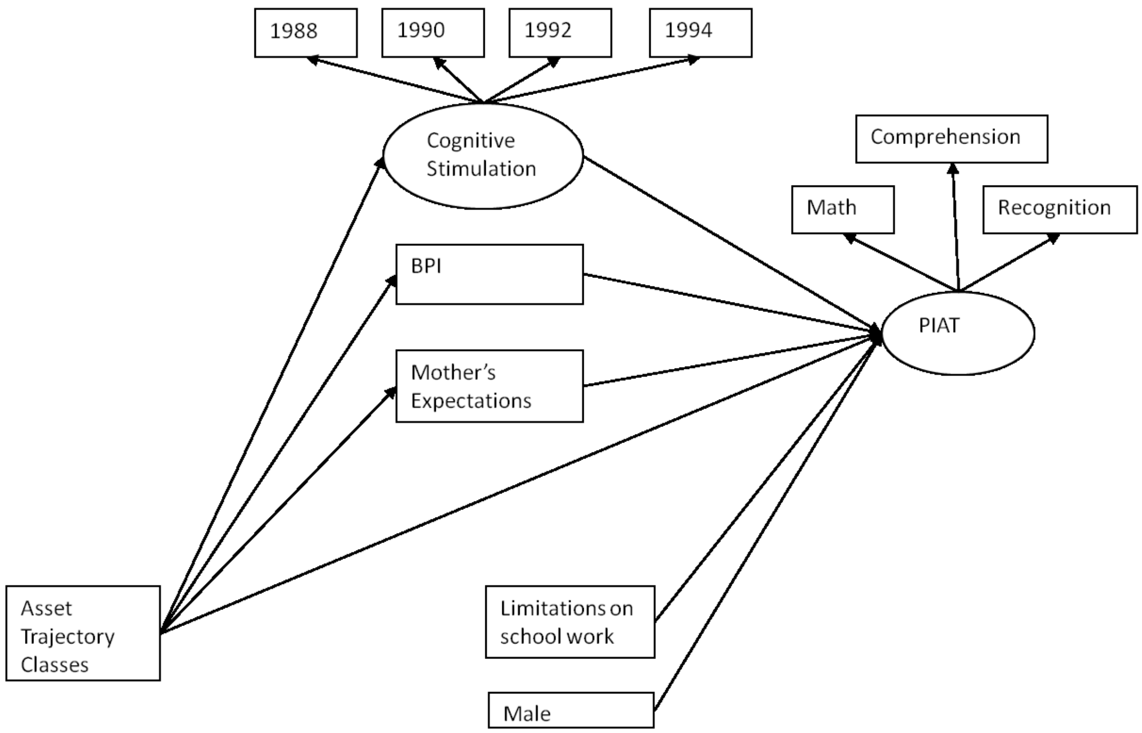

Figure 5. PIAT Mediated Pathway Analytic Model

For the high school model, the dichotomous high school graduation status is regressed on the asset trajectory class memberships obtained from the early-mid childhood GMM, on children's educational aspirations and the latent variable for the quality of home cognitive stimulation. To test the latter two variables as possible mediators, these variables are also regressed on the asset trajectory classes. Included in the model as control variables are the children's standardized scores for PIAT Math, PIAT Reading Comprehension, PIAT Reading Recognition and BPI, mother's expectations, gender, and limitations on school work. The analysis model is shown in figure 6.

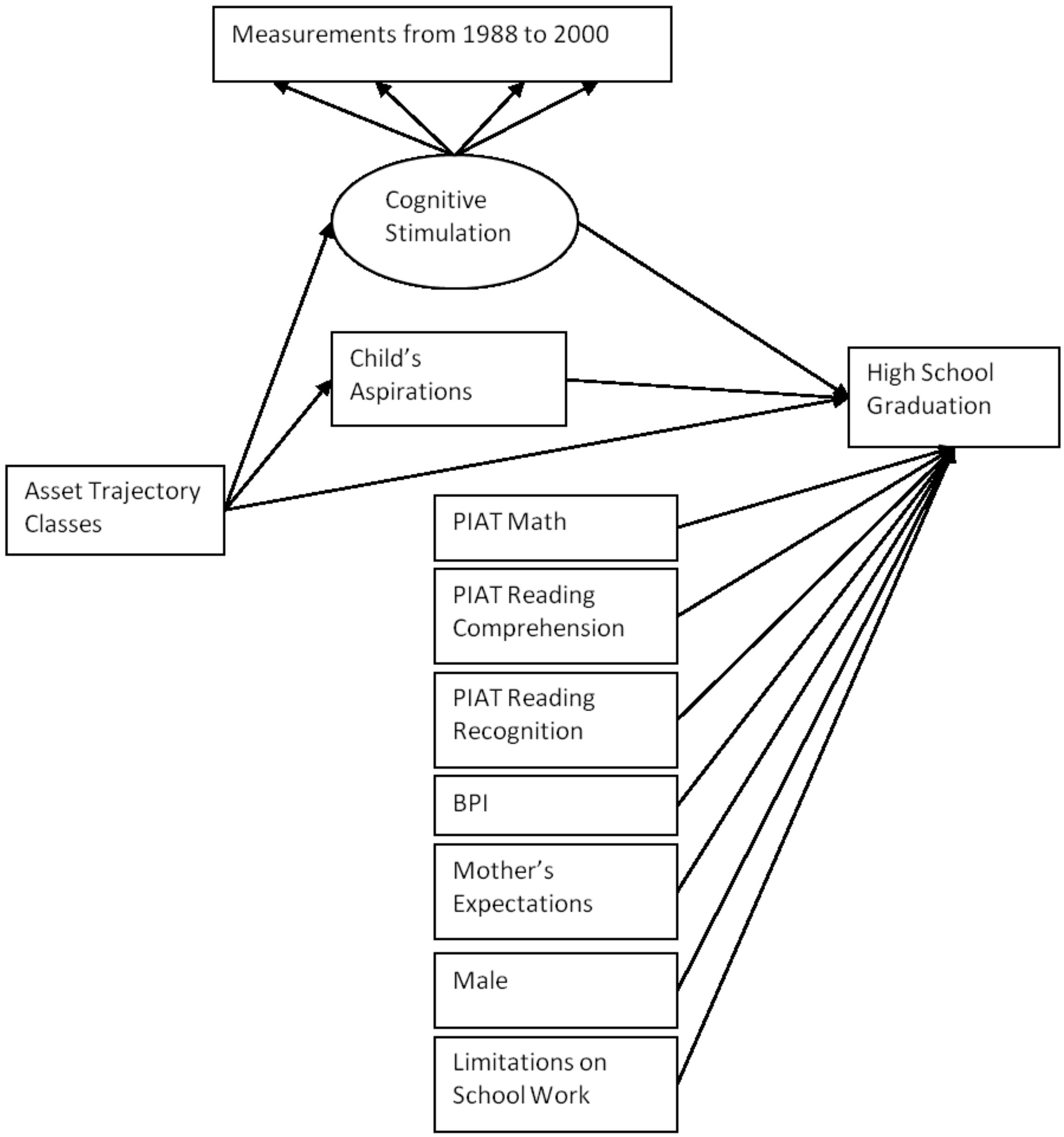

Figure 6. High School Mediated Pathway Analytic Model

Analytic Model for Research Aim 4

The fourth research aim seeks to test whether the timing of when asset accumulation matters with regard to children's high school graduation outcomes. For this research aim, a two-class conditional GMM for asset accumulation is first estimated to model asset accumulation for the early childhood years from 1987 to 1993. As a general increasing trend in net worth over time was observed for the sample, one class models a stable asset trajectory and the other models an increasing asset trajectory. A second two-class GMM is then estimated for the middle childhood years from 1994 to 2000, incorporating the class assignment from the first model as known classes to model the trajectories for the early childhood period (see figure 7). The result is a four-class model, with one class representing a stable asset trajectory throughout early and middle childhood, a class representing a stable trajectory during early childhood and an increasing trajectory during middle childhood, a third class representing an increasing trajectory in early childhood and a stable pattern in middle childhood, and the last class representing an increasing trajectory through early and middle childhood.

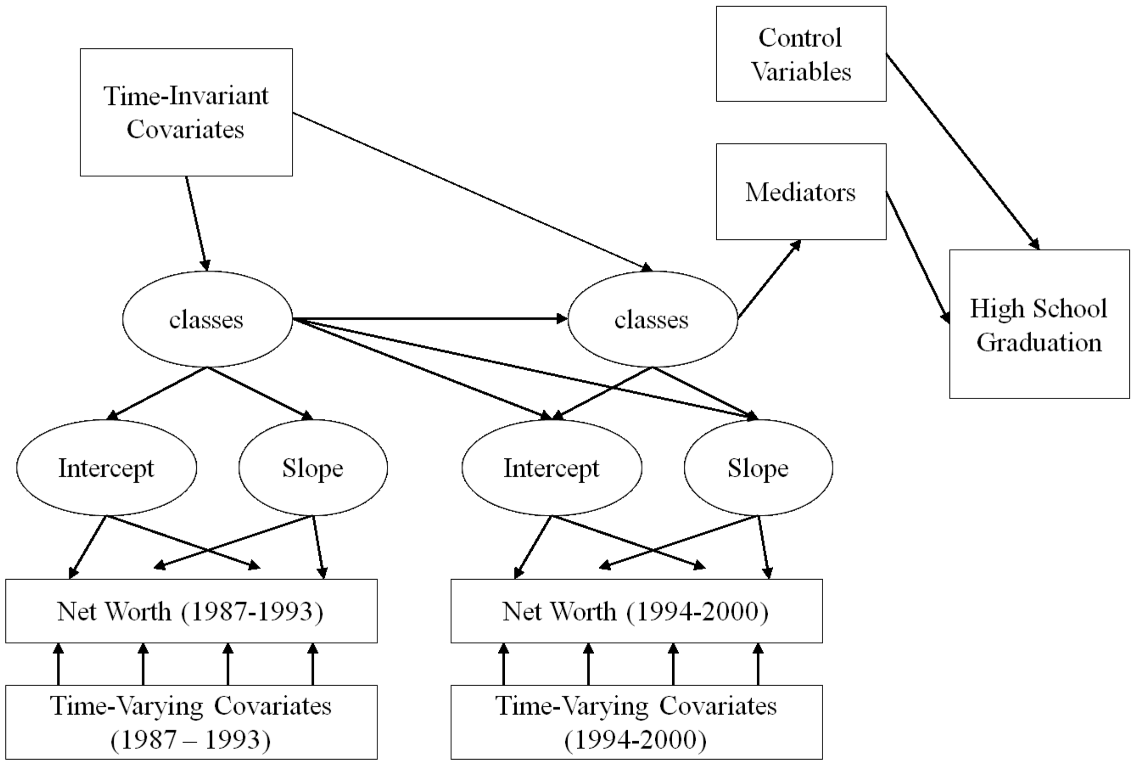

Figure 7. Analytic Model on Timing and the Assets Effect on High School Graduation

A structural equation model using the class assignments derived from the four-class model is then estimated to compare the effects of assets on the odds of high school graduation across the different asset trajectory classes, mediated by the quality of the home cognitive stimulation and child's educational aspirations, and adjusting for PIAT scores in math and reading at around third grade, gender, mother's expectations, school work limitations, and the BPI scores. Other than the difference in asset trajectory class assignments, the analytic model is the same as depicted in figure 6.

V Results

Sample

Of the 9684 children in the merged NLSY79 and NLSY79-CYA dataset, data on 1036 children born in 1986 (516 children) and 1987 (520 children) were analyzed, with standard errors adjusted by using the subpopulation command in Mplus (Graubard & Korn, 1996; Korn & Graubard, 1999)[1]. Customized sampling weights that are created for children who were surveyed in 1996, 2004 or 2006 are used, with a weight of zero assigned to the 95 cases that were not interviewed in all three years. A comparison of means revealed that children with zero weights are not statistically different from children with non-zero weights with respect to mother's characteristics such as being

[1] A growth mixture model using the sub-population command with the full sample was compared against a model containing just the sub-population of interest. Both models yielded identical model information criterion and coefficients. Standard errors, however are different, in accordance with expectations.

non-black/non-Hispanic (t = 1.29), marital status (t = -.61) and employment status (t = -.24), both measured in the first survey year of 1987. Household characteristics between children with zero and non-zero weights are also similar with regard to total net family income (t = -.32) and household net worth (t = .43), again both measured in 1987.

A comparison of means between children with valid and missing observations on the outcome variables also indicated that there is no statistical difference between the two groups. For those with missingness on the PIAT Math standardized scores, there is no statistical difference in mother's characteristics such as being non-black/non-Hispanics (t - .11), marital status (t = .04), employment status (t = 1.46), and mother's expectations for their children's education (t = .71). Household characteristics measured in 1987 are also similar with regard to total net family income (t = 1.76) and family net worth (t = -.64), and in the quality of cognitive home stimulation (t = .50) measured in 1988. Child characteristics are also similar with regard to BPI scores (t = -.79) and limitations on school work (t = -1.19), both measured in 1996.

Items with missing values, either as a result of non-response or due to non-interview, are hence assumed to be missing at random. Missing values, with the exception of the variable in the number of children in the household, were then imputed. An inspection of the weighted means of the variables between the original and the imputed datasets indicated that they are very similar (see Appendix 3).

In the final sample, 78 percent of the mothers are non-black/non-Hispanic, 14 percent are African-American, and 8 percent Hispanic. The mean age at their child's birth was 25.7 years. In 1987, the first survey year, 81 percent were married while 49 percent reported being employed. In 2000, mothers who reported being married fell to 68 percent, while 87 percent reported being employed. Also in 2000, the mean number of children in the household was 2.5, and 50 percent of households reported having at least one parent with an Associate Degree or higher. Mean household net worth in 1987 was around $33,000, increasing to around $115,000 in year 2000. [2]

As for household income, the mean for the sample increased from around $42,000 (in 2000 dollar value) to around $52,000 from 1987 to year 2000. In 1987, about 20

[2] Not including assets and debts associated with homeownership, the adjusted mean household net worth in 1987 was around $15,800 (2000 dollar value), increasing to around $64,500 in year 2000.

percent of the sample had household incomes of less than $18,000 (year 2000 dollar value) while about 50 percent had incomes of less than $38,000. [3]

With regard to children's characteristics, 51 percent are male, 4 percent reported having limitations on school work, and 64 percent graduated from high school by 2006. Appendix 3 lists the weighted means of all the variables used in this study.

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[3] In comparison, the mean household income for the general population in the United States in 1987 was slightly over $49,000 (in year 2000 dollar value) (U.S. Census Bureau, 2008), while the poverty guideline for a family of four in that year was just under $17,000 (U.S. Department of Health & Human Services, 2009).

Research Aim 1:

What are the asset accumulation trajectories for households with children?

Early Childhood Asset Trajectories

Asset trajectories for households with young children over the early childhood stages of the child's life is estimated using the household net worth data from 1987 to 1993, from around the time of the child's birth or age 1, to when the child is age 6 or 7. One-class latent growth curve models with linear and quadratic growth trajectories were first estimated to determine whether a linear or quadratic slope would better represent the data. Using the guidelines suggested by Hu and Bentler (1999), the results indicate that the latent growth curve model with a linear slope has a poor model fit. On the other hand, the model with a quadratic slope factor has a reasonable model fit, with CFI value of .995, TLI value of .994, and a RMSEA value of .016. A quadratic slope is assumed for subsequent model estimation. The comparison of the model fit statistics is presented in table 1.

Table 1.

Model Fit Statistics for One-Class Unconditional Latent Growth Curve Model for Early Childhood

	Linear LGC model	Quadratic LGC model
CFI	.846	.995
TLI	.856	.994
RMSEA	.085	.016

Growth mixture models with quadratic growth shape for each class were then estimated, starting with two classes. The two-class model resulted in smaller information criteria compared to the one-class model. In addition, the Adjusted LRT yielded significant results (Adjusted LRT = 294760.68, p = .011), indicating that the one-class model should be rejected in favor of the two-class model. Three-, four- and five-class growth mixture models with quadratic slope factors in each latent class were then estimated. A comparison of the models showed that the information criteria became smaller with when moving from the two-class to three, then to the four class models, indicating a better model fit for models with more classes. The Adjusted LRT was also significant for each model, again indicating that the models with the larger number of classes are better. However, with the five-class model, while the information criteria were smaller compared to the four-class model, entropy fell from 0.974 to 0.950 indicating poorer classification, and the Adjusted LRT was not significant (Adjusted LRT = 284841.13, p = .09). Taken together, the results suggest that the four-class model could not be rejected in favor of a five-class model. As such, the four class solution was selected as the optimal model to develop the conditional model with covariates included. The summary of the model comparison is presented in table 2.

Table 2.

Fit Indices, Entropy, and Model Comparisons for Estimated Growth Mixture Models for Early Childhood

	Log Likelihood	AIC	BIC	SABIC	Entropy	Adjusted LRT
One-class	-18101.28	36232.55	36306.70	36259.06	-	-
Two-class	-17806.76	35651.52	35745.43	35685.01	.964	294760.68*
Three-class	-17648.54	35343.08	35456.77	35383.71	.957	289708.72**
Four-class	-17514.73	35083.46	35216.92	35131.17	.974	287096.46*
Five-class	-17418.90	34899.91	35053.04	34954.59	.950	284841.13
Four-class[a]	-16429.62	32973.25	33252.25	33071.21	.958	274160.389*
Five-class[a]	-16309.82	32749.65	33067.80	32861.36	.958	271995.993

Note: [a] Conditional models with covariates; * $p < .05$; ** $p < .01$

To properly specify the optimal number of latent classes as well as to correctly assign class membership, Muthén (2004; 2006) argues that covariates need to be included in the model estimation. A four-class conditional model is thus estimated with the socio-economic background characteristics of the household and of the mother added as either time-varying or time-invariant covariates. The time-varying covariates in the model are total net family income and the marital and employment status of the mother in the household, while the race and age of the mother in 1986, and the human capital of parents and the number of children in the household in 1993, are included as time-invariant covariates.

The results indicate that the four-class conditional model has reasonable model fit, with a significant Adjusted LRT (mean = 274160.389, p = .02). When a five-class conditional model was attempted, the model reported non-significant Adjusted LRT values, indicating that the 4-class model cannot be rejected in favor of this model. The four-class solution is therefore adopted as representing the optimal structure, number, and membership of classes inherent in the data.

Table 3.

Growth Factor Means for the Early Childhood Growth Mixture Model

	Intercept Factor		Linear Factor		Quadratic Factor	
	b	SE	b	SE	b	SE
LS	-0.109	0.318	0.344	0.251	-0.052	0.036
LA	2.562	2.04	-1.344	.667*	0.661	.108 ***
HS	8.205	1.188***	4.557	2.903	-0.789	.452#
HA	7.17	1.101 ***	6.628	1.662 ***	-0.704	.289 *

Note: LS – Low Stable Class; LA – Low Accumulator Class; HS – High Stable Class; HA – High Accumulator Class

# p < .10; * p < .05; *** p < .001;

Two general growth trends are observed from the four classes that have been identified through the growth mixture model. The first is a relatively stable trend with non-significant latent growth factors, and the second is a trend reflecting significant linear and/or quadratic growth factors. There are also two clusters in terms of initial asset values, a cluster with initial asset values that are not significantly different from zero, and the other with initial asset values that are significantly higher than zero. With different initial levels of assets and rates of change, the four asset trajectory classes can be described as Low Stable (LS), with initial levels of assets that are not significantly different from zero, and with non-significant growth factors (see table 3); Low Accumulator (LA) with initial asset levels are that are also not significantly different than zero, but with significant linear and quadratic growth trends; High Stable (HS) with initial asset levels that are significantly higher than zero and relatively stable growth trends; and High Accumulator (HA) with levels of initial assets significantly higher than zero, with significant rate of asset growth. In terms of class memberships, 81 percent of children belong to the Low Stable class, 4 percent to the Low Accumulator class, 9 percent to the High Stable class, and 6 percent to the High Accumulator class.

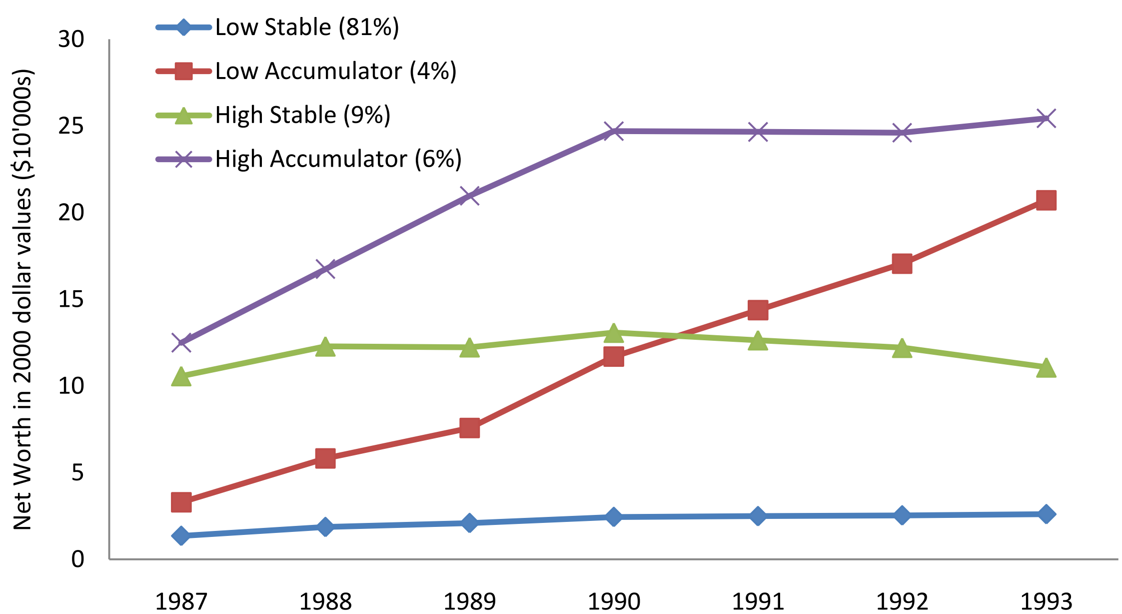

Figure 8. Asset trajectories for Early Childhood

The observed net worth values across the different time points of the four classes are shown figure 8. In addition to between-class differences, growth mixture modeling also allows for within-class variation in individual trajectories around the class mean. In other words, within the same trajectory class, individual members may have different initial levels of asset and rates of change, reflecting both increases and possibly declines in net worth over time. The variations in observed individual household net worth trajectories around the estimated class means for each latent class, illustrated using one of the imputed datasets, are shown in figures 9 to 12.

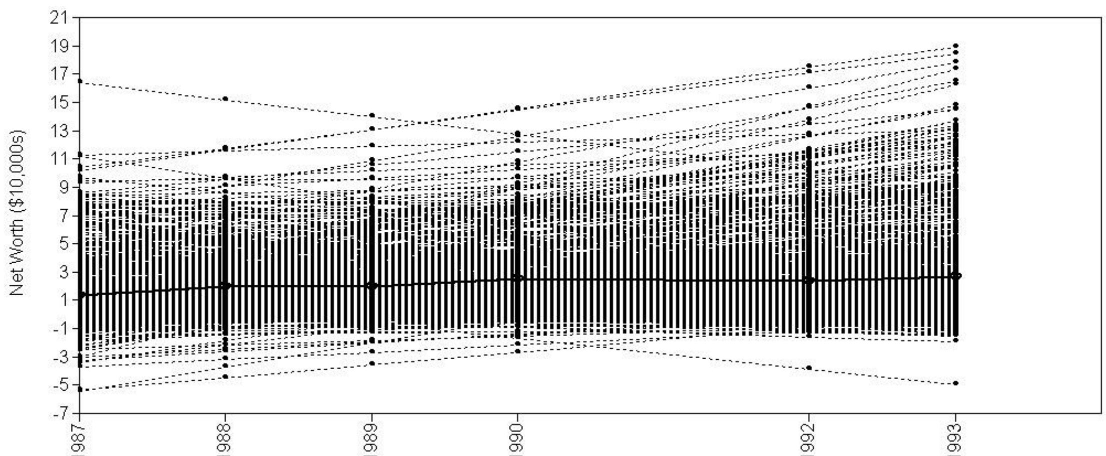

Figure 9. Estimated Means and Observed Fitted Individual Values for the Low Stable Class in Early Childhood

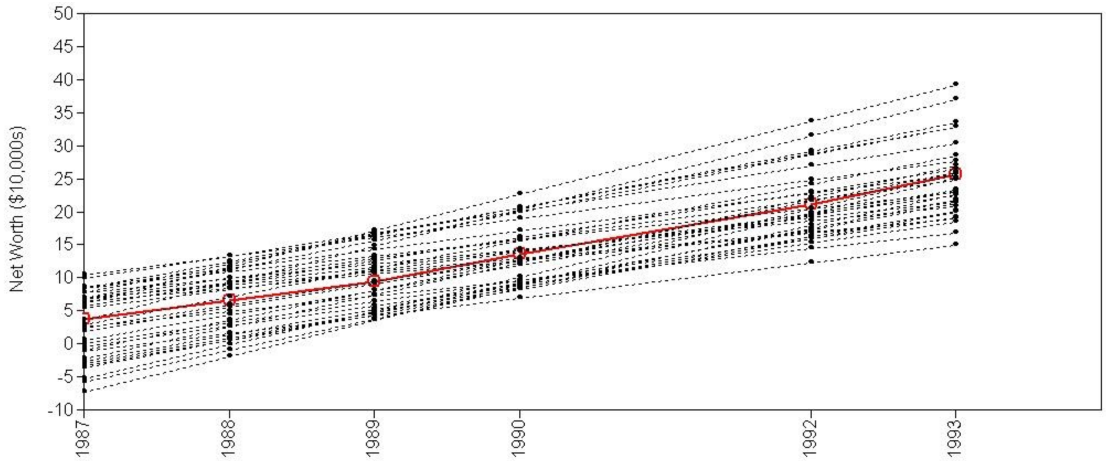

Figure 10. Estimated Means and Observed Fitted Individual Values for the Low Accumulator Class in Early Childhood

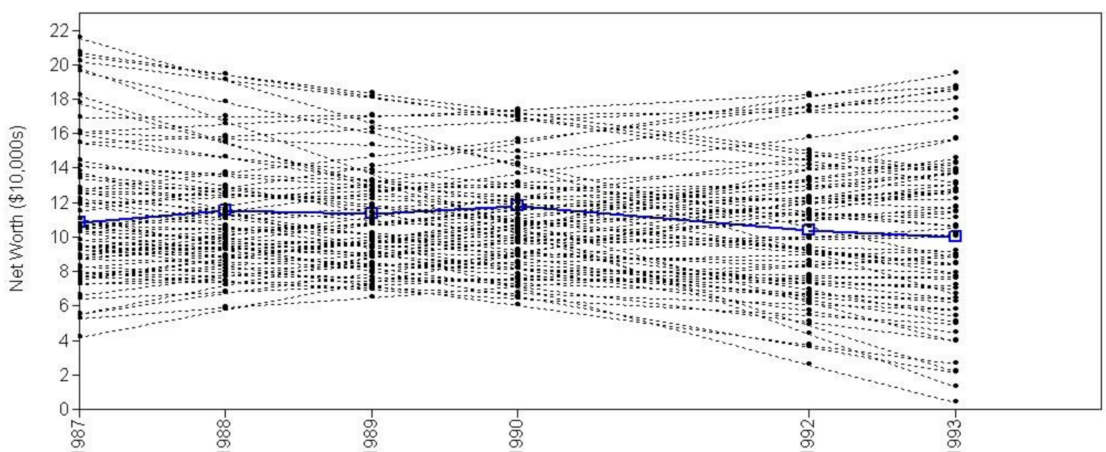

Figure 11. Estimated Means and Observed Fitted Individual Values for the High Stable Class in Early Childhood

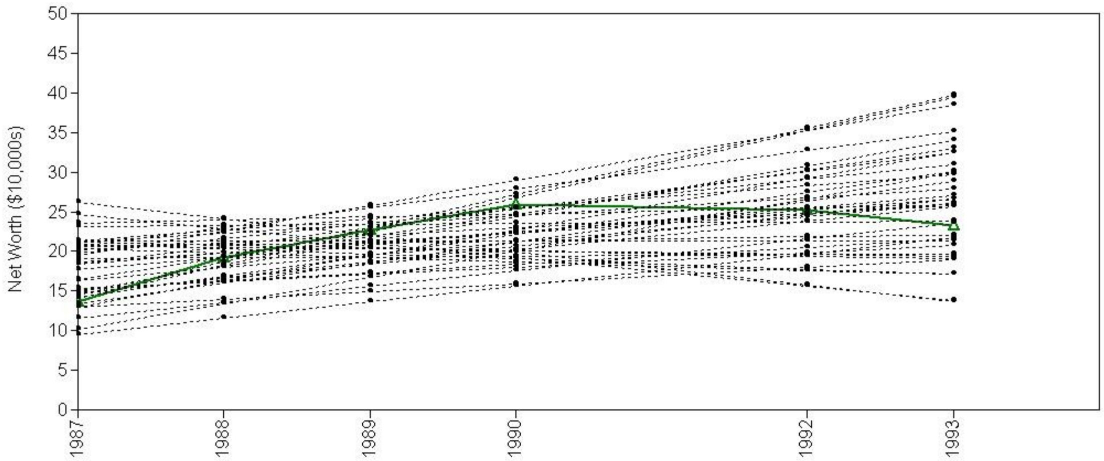

Figure 12. Estimated Means and Observed Fitted Individual Values for the High Accumulator Class in Early Childhood

Table 4 presents the estimated logistic coefficients of the time-invariant covariates on the latent-class variable. Adjusting for the other covariates, mother's age is significantly and positively related to the log odds of being in the High Stable class compared versus being in the Low Stable class (b = .3542, p < .05), but no significant relationship is observed when the Low Stable class is compared to the Low Accumulator or High Accumulator classes. In other words, mothers in the High Stable class tend to be older than in the Low Stable class, adjusting for other covariates in the model.

Mother's race is also significantly associated with latent class membership, adjusting for the other covariates in the model. The log odds of a non-black/non-Hispanic mother being in the Low Accumulator (b = 1.218, p < .05) and High Accumulator (b = 2.8016, p < .01) classes are significantly higher than being in the Low Stable class. No significant difference is observed between the Low Stable and High Stable classes in this regard. Similarly, adjusting for other covariates in the model, households where at least one parent has an Associate Degree or higher have significantly higher odds of being in the Low Accumulator ($b = 1.82, p < .01$) and High Accumulator ($b = 1.81, p < .01$) classes versus being in the Low Stable class. Low Stable and High Stable classes are not significantly different in this regard. [4]

[4] An alternative model using the variable on mothers', instead of parents', educational attainment was also attempted. The models yielded almost identical class assignments and substantive outcomes. As the focus of this study is to estimate trajectories based on net worth at the household level, parental educational information, rather than mother's, was used instead.

Table 4.

Logistic Coefficient Estimates for Predictors on the Latent-Class Variable (Early Childhood Model)

	Latent Classes		
	Low Accumulator	High Stable	High Accumulator
	mean b	mean b	mean b
Mother's Age	-0.156	0.3542*	0.2832#
Mother's is non-black/non-Hispanic	1.218*	2.0548#	2.8016**
Number of Children in Household'93	0.4992#	0.1848	0.4044#
Parents with at least Associate Degree'93	1.8244**	0.6338	1.8056**

Note: The reference class in this multinomial estimation is the Low Stable Class.

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

Early-Mid Childhood Asset Trajectories

To model the growth trajectories of household net worth from 1987 to 2000, unconditional one-class latent growth curve models with linear and quadratic slopes were first estimated and model fit indices compared to determine the shape of the growth factors. The results indicate that the latent growth curve model with a quadratic slope has better model fit compared to the model with a linear slope. In fact, using the guidelines suggested by Hu and Bentler (1999), the unconditional one-class linear latent growth curve model would be evaluated as not meeting the criteria for adequate model fit. Table 5 presents the model fit statistics for the one-class unconditional latent growth curve models.

Table 5.
Model Fit Statistics for One-class Unconditional Latent Growth Curve Models for Early-Mid Childhood.

	Linear LGC model	Quadratic LGC model
CFI	.877	.925
TLI	.889	.927
RMSEA	.065	.053

Next, a two-class growth mixture model was estimated with quadratic growth shape in each latent class. As can be seen in table 6, this model resulted in smaller information criteria compared to the one-class model. In addition, the Adjusted LRT yield significant results (Adjusted LRT = 521974.21, p = .000), indicating that the one-class model should be rejected in favor of the two-class model.

A three-class and then a four-class growth mixture model with quadratic growth shape in each latent class were estimated next. Comparing the two-, three- and four-class models, the model with k classes had smaller information criteria compared to the k-1 class models. The adjusted LRT also yielded significant results for the k-class models, indicating that the k-1-class models should be rejected in favor of the k-class models (see table 6). A five-class growth mixture model with quadratic growth shape in each latent class was also estimated. However, this model had various convergence problems with several of the implicates reporting local maxima issues and failing to obtain global solutions. Hence the four-class solution was selected as the optimal unconditional growth mixture model.

Table 6.

Fit Indices, Entropy, and Model Comparisons for Estimated Growth Mixture Models for Early-Mid Childhood

	Log Likelihood	AIC	BIC	SABIC	Entropy	Adjusted LRT
One-class	-32084.82	64207.638	64301.557	64241.211	-	-
Two-class	-31816.57	63679.137	63792.829	63719.778	0.962	521974.21***
Three-class	-31660.42	63374.836	63508.300	63422.545	0.952	517396.27*
Four-class	-31556.89	63175.778	63329.015	63230.555	0.954	514756.79***
Four-class with predictors	-26554.62	53255.237	53605.078	53373.244	0.953	450996.833**

Note: * $p < .05$; ** $p < .01$; ***$p < .001$;

Like in the early childhood growth mixture model, a four-class conditional model was estimated, with the socio-economic background characteristics of the household and of the mother added as either time-varying or time-invariant covariates. The time-varying covariates in the model are total net family income and the marital and employment status of the mother in the household, while the race and age of the mother in 1986, and the human capital of parents and the number of children in the household in 2000, are included as time-invariant covariates. The results of the model indicates that the four-class conditional model has reasonable model fit as well, with a significant Adjusted LRT (mean = 450996.833, $p < .01$). When a five-class conditional model was attempted, the model reported singularity issues and failed to converge. This is considered an indication of model misfit, and can be used as evidence that the model with one fewer classes is superior (Nylund et al., 2007). A four-class solution is therefore adopted, and the parameter estimates for the growth factors are presented in table 7.

Table 7.

Growth Factor Means for the Early-Mid Childhood Growth Mixture Model

	Intercept Factor		Linear Factor		Quadratic Factor	
	b	SE	b	SE	b	SE
LS	-0.144	0.21	0.086	0.128	-0.002	0.013
LA	-0.206	1.284	4.007	1.062***	-0.188	.111#
HS	8.884	.697***	-0.387	0.292	0.038	0.038
HA	11.709	1.111***	2.172	.517***	-0.084	0.063

Note: LS – Low Stable Class; LA – Low Accumulator Class; HS – High Stable Class; HA – High Accumulator Class

# p < .10; *** p < .001;

The structure and class membership of this model is very similar to that of the early childhood model. Two general growth trends are also observed from the four classes that have been identified through the growth mixture model. The first is a relatively stable trend with non-significant latent growth factors and the second is a trend reflecting significant growth trends in the rates of asset accumulation. There are also two clusters of initial asset values, one with initial asset levels that are not significantly different from zero, and the second with initial levels that are significantly higher than zero. With different initial levels of assets and rates of change, the four asset trajectory classes can be described as Low Stable (LS), with a lower initial asset levels that are not significantly different from zero and with a non-significant stable rate of growth; Low Accumulator (LA) with initial asset levels that are also not significantly different from zero but with a significant rate of accumulation; High Stable (HS) with the initial levels of assets that are significantly higher from zero but with a relatively non-significant stable growth trend; and High Accumulator (HA) with initial levels of assets significantly higher than zero and with a significant rate of asset growth over time. In terms of class memberships, 77.8 percent of children belong to the Low Stable class, 4.3 percent to the Low Accumulator class, 11.9 percent to the High Stable class, and 6.1 percent to the High Accumulator class. The observed net worth values for the four classes are shown figure 13.

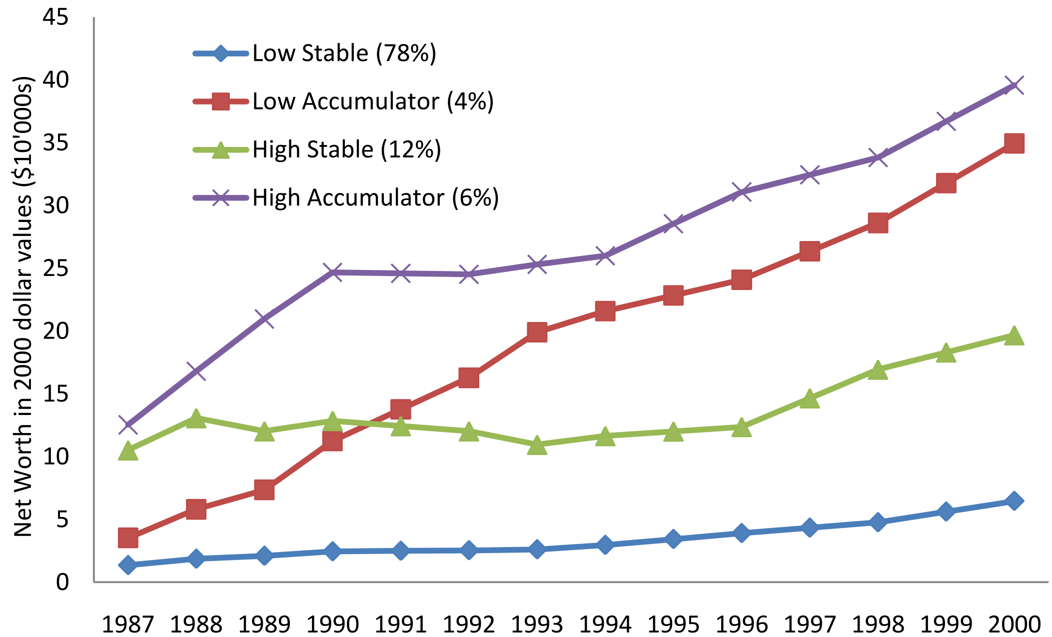

Figure 13. Asset Trajectories for Early - Mid Childhood

Using one of the imputed datasets, the variations in observed individually fitted household net worth values around the model estimated mean of each latent asset trajectory class are presented in figures 14 to 17.

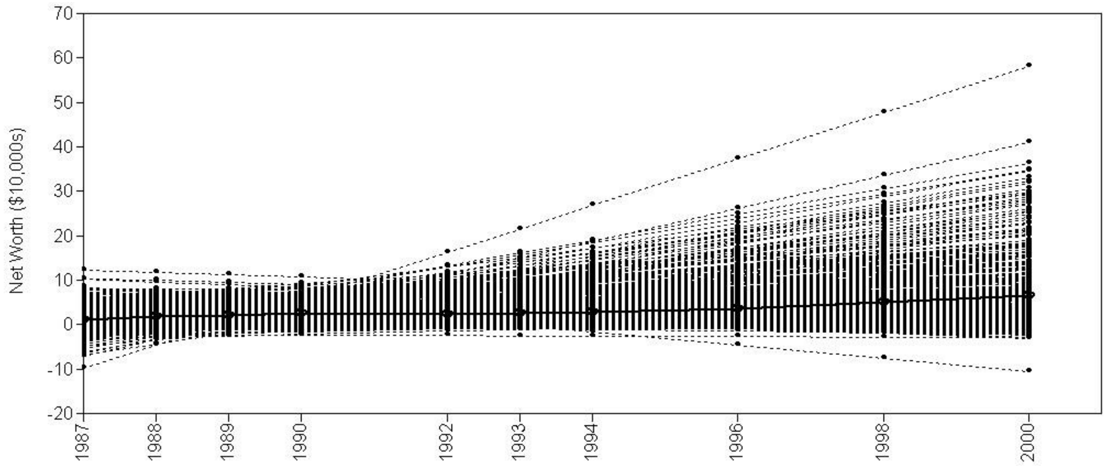

Figure 14. Estimated Means and Observed Fitted Individual Values for the Low Stable Class in Early-Mid Childhood

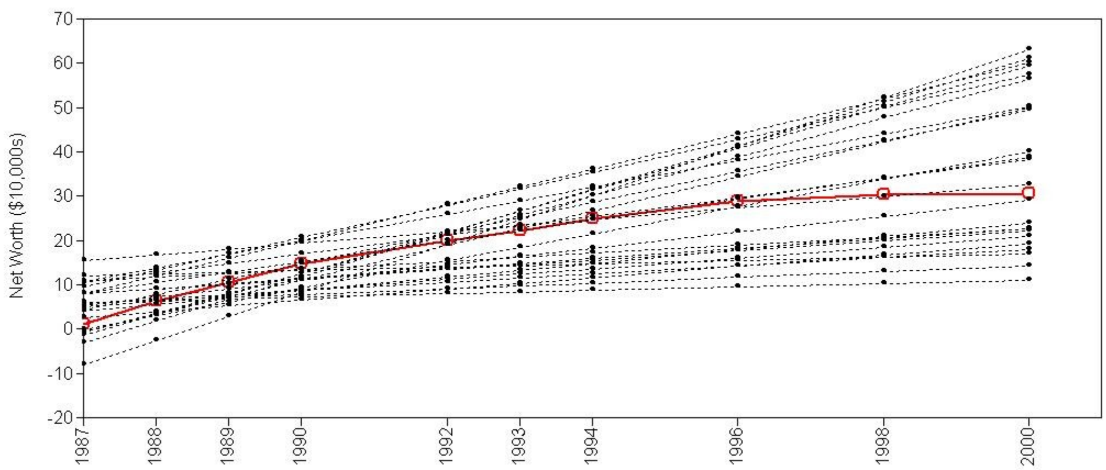

Figure 15. Estimated Means and Observed Fitted Individual Values for the Low Accumulator Class in Early-Mid Childhood

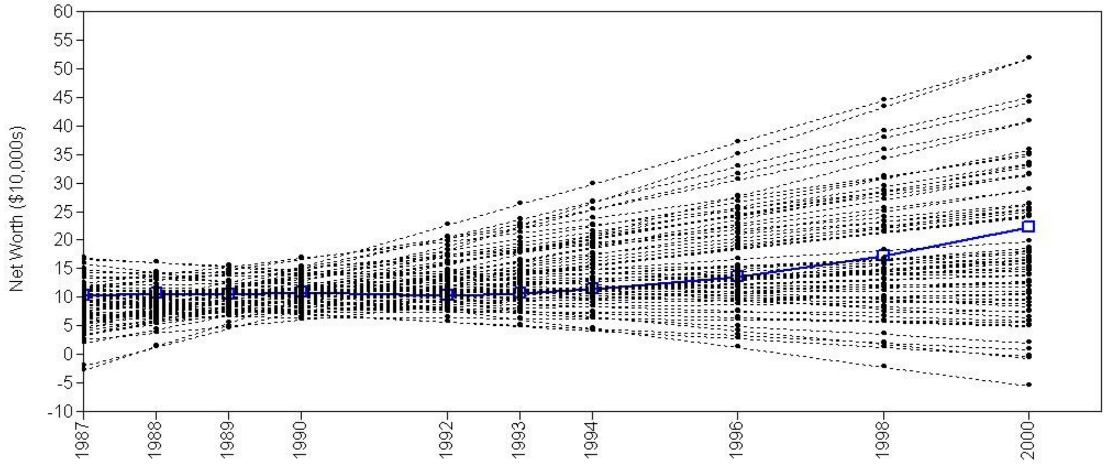

Figure 16. Estimated Means and Observed Fitted Individual Values for the High Stable Class in Early-Mid Childhood

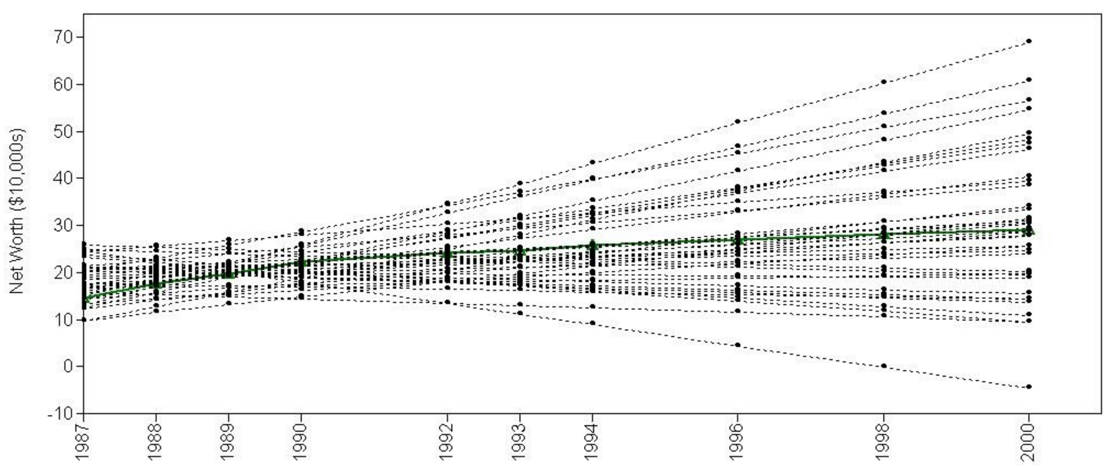

Figure 17. Estimated Means and Observed Fitted Individual Values for the High Accumulator Class in Early-Mid Childhood

Adjusting for total net family income, maternal employment and marital status at each time point, older mothers have significantly higher log odds of belonging to the High Stable ($b = .339$, $p < .01$) and High Accumulator ($b = .327$, $p < .01$) classes than belonging to the Low Stable class. No significant maternal age difference is observed between the Low Stable and Low Accumulator classes. Mothers who are non-black/non-Hispanic also have significantly higher log odds of belonging to the Low Accumulator ($b = 1.222$, $p < .05$), High Stable ($b = 2.111$, $p < .001$) and High Accumulator ($b = 2.523$, $p < .05$) classes than belonging to the Low Stable class, adjusting for the other covariates in the model.

In addition, households with at least one parent having an Associate Degree or higher in 2000 have higher log odds of belonging to the Low Accumulator ($b = 1.553$, $p < .01$) and High Accumulator ($b = 1.567$, $p < .05$) classes than to the Low Stable class. There is no difference in the parents' human capital between the Low Stable and High Stable classes. In other words, the results suggest that higher human capital is positively associated with belonging to asset trajectory classes that have significant growth trends, adjusting for the other covariates in the model.

Finally, households with more children have significantly higher log odds of belonging to the High Accumulator ($b = .46$, $p < .05$) class compared to the Low Stable class, adjusting for the other covariates in the model.   No significant difference in the number of children in the household is observed between the Low Stable and Low Accumulator, and Low Stable and High Stable classes respectively.

Table 8.

Logistic Coefficient Estimates for Predictors on the Latent-Class Variable (Early-Mid Childhood Model)

	Low Accumulator	High Stable	High Accumulator
	mean b	mean b	mean b
Mother's Age	0.0824	0.3394**	.3274*
Mother's is non-black/non-Hispanic	1.2224*	2.1106***	2.5234*
Number of Children in Household'00	.023	.1344	.46*
Parents with at least Associate Degree'00	1.553**	.4718	1.5674*

Note: The reference class in this multinomial estimation is the Low Stable Class.

* $p < .05$; ** $p < .01$; *** $p < .001$

Research Aims 2 and 3:

What are the effects of different asset accumulation trajectories on educational outcomes: Direct and mediated?

For the research aims of exploring (i) whether the different asset trajectories are associated with better educational outcomes in terms of PIAT test scores at ages 9 or 10, and odds of graduating from high school by ages 19 or 20; and (ii) whether the mediating pathways for the relationship between asset and educational outcomes are different based on membership in the asset trajectory classes, two structural equation models (SEM) are estimated using Mplus. The first models the effects of assets on PIAT outcomes using the asset trajectory classes estimated over the early childhood stage of the child from birth to ages 5 or 6 (see figure 3). The second model estimates the effects of assets on high school graduation using net worth data spanning early to middle childhood from birth to ages 13 or 14 (see figure 4).

The major advantages of the SEM approach include their ability to test the mediation hypothesis as well as the ability to account for some correlated errors in predictors arising from repeated measurement (McCartney et al., 2006). The estimated paths in the SEM also test direct and indirect associations among the latent variables, and between the latent variables and other covariates, and with other proximal or distal outcomes(McCartney et al., 2006).

Asset Trajectories and Children's PIAT Outcomes

Data on 1036 children and their mothers using the five implicates from the multiple imputation process were analyzed to estimate the direct and indirect effects on assets on children's PIAT outcomes. Of these children, 78 percent are classified as belonging to the Low Stable (LS) asset trajectory class, 4 percent from the Low Accumulator (LA) trajectory class, 12 percent from the High Stable (HS) asset trajectory class, and 6 percent from the High Accumulator (HA) class. Asset trajectory class assignments are obtained from the GMMs estimated for research aim 1. The weighted means of the analysis sample is detailed in Table 9. As can be seen from the table, there is a general increasing trend for PIAT outcomes as one moves from the Low Stable class, to Low Accumulator, High Stable, and finally to the High Accumulator asset trajectory classes. The same general trend is observed for mother's educational expectations for her child, and for the home cognitive stimulation measures across the various time points. There is also a general decreasing trend for scores on the Behavior Problems Index (BPI), indicating fewer behavioral problems exhibited by children as asset levels increase. The classes were also dummy coded and the means of each class was compared against the means of the rest of the sample using independent samples T-tests. The results indicate that for most of the indicators, the means of child within any particular class are significantly different from children who are not in the same class. In addition, children from the Low Stable class have significantly lower scores for the three PIAT subtests compared to children who are not in the Low Stable class (see Table 9).

Table 9.

Descriptives of Early Childhood Sub-Population

	Latent Asset Trajectory Classes			
	LS[c]	LA[c]	HS[c]	HA[c]
Outcome Measures[a]				
PIAT Math	102.6***	107.29***	108.21***	110.05***
	(0.74)	(2.97)	(2.26)	(2.76)
PIAT Reading Recognition	104.25***	107.61*	110.74***	111.44***
	(0.69)	(2.41)	(2.62)	(2.61)
PIAT Reading Comprehension	101.91***	103.41	107.53***	107.83***
	(0.67)	(2.2)	(2.14)	(2.44)
Mediating Variables[a]				
Mother's Expectations	3.58***	3.87**	3.94***	3.98***
	(0.05)	(0.22)	(0.13)	(0.17)
BPI	106.32***	102.68	99.51***	102.13**
	(0.75)	(3.57)	(2.29)	(2.69)
Home Cognitive	100.42***	106.10***	105.49***	107.35***
Stimulation'88	(0.70)	(2.84)	(3.20)	(2.21)
Home Cognitive	98.51***	103.33***	105.46***	106.55***
Stimulation'90	(0.76)	(2.77)	(2.20)	(1.76)

	Latent Asset Trajectory Classes			
	LS[c]	LA[c]	HS[c]	HA[c]
Home Cognitive	98.13***	106.52***	106.14***	107.35***
Stimulation'92	(0.71)	(2.65)	(1.72)	(1.86)
Home Cognitive	98.32***	106.61***	107.63***	109.44***
Stimulation'94	(0.75)	(2.62)	(1.91)	(1.96)
Control Variables[b]				
Limitations on School Work	0.04	0.08	0.02	0.00***
	(0.01)	(0.07)	(0.03)	(0.00)
Male	0.51	0.42*	0.56	0.48
	(0.02)	(0.12)	(0.08)	(0.12)
Other Background Variables[b]				
Non-black/Non-Hispanic	0.74***	0.90***	0.96***	0.98***
	(0.02)	(0.05)	(0.02)	(0.02)
Parents with at least Some	0.34***	0.73***	0.54***	0.79***
College Education	(0.02)	(0.10)	(0.09)	(0.09)

Notes: LS – Low Stable class (n = 808); LA – Low Accumulator class (n = 30); HS – High Stable class (n = 55); HA – High Accumulator class (n = 35)

[a] Weighted means with the mean standard error in parenthesis

[b] Weighted proportions with the mean standard error in parenthesis

[c] Members of each class are compared against non-members using independent sample T-tests or Chi-square tests. Significant findings are indicated where * p < .05, ** p < .01 and *** p < .001

For this analysis, the PIAT Math, PIAT Reading Recognition, and PIAT Reading Comprehension standardized scores measured in 1996 are constructed as a continuous latent variable as they measure the underlying academic achievement of children (Center for Psychological Studies, n.d.; Klinge et al., 1974). The quality of cognitive stimulation in the home environment measured in 1988, 1990, 1992 and 1994 are also constructed as a continuous latent variable. In this model, the outcome is the latent PIAT outcome and the predictors are the asset trajectory classes. Included as mediators in the model are the latent home cognitive stimulation variable, BPI standardized scores measured in 1996, and mothers' expectations for their children's education, also measured in 1996. In addition, the child's gender and whether there were limitations on school work in 1996 are added as control variables.

The model estimating the effects of asset trajectories on children's PIAT outcomes at ages 9 or 10 has a reasonable model fit, with the mean $\chi2 = 145.76$ (SD = 12.64, DF = 54), mean CFI = .959 (SD = .006), mean TLI = .939 (SD = .008) and mean RMSEA = .04 (SD = .003). The latent variable for the quality of home cognitive stimulation from birth to ages 6 or 7 is found to be significantly associated with the latent variable for the three PIAT subtests ($b = .409$, $p < .001$). Mother's educational expectations for her child ($b = 2.719$, $p < .001$) and the child having limitations on school work ($b = -13.268$, $p < .001$) are also significantly associated with PIAT outcomes. The child's score on the Behavioral Problems Index, and being male, however, are not significantly associated with PIAT outcomes. The results also indicate that in terms of the direct effects of assets accumulation on PIAT, there are no significant differences between the trajectory classes when either Low Stable or Low Accumulator trajectory classes are used as the reference group.

The results further indicate that the relationship between assets and PIAT outcomes is fully mediated by the quality of cognitive stimulation in the home environment and the level of mother's educational expectations for her child, and that the nature of the relationship differs across the different asset accumulation classes. Consistent with expectations, children in the Low Accumulator class ($b = 5.291$, $p < .001$), the HS class ($b = 5.790$, $p < .001$), and children from the High Accumulator class ($b = 6.864$, $p < .001$) have significantly higher quality of cognitive stimulation in the home environment compared to children in the Low Stable class. Mothers of children from the High Stable and the High Accumulator asset trajectory classes also had significantly higher educational expectations for their children compared to mothers of children from the Low Stable asset trajectory class.

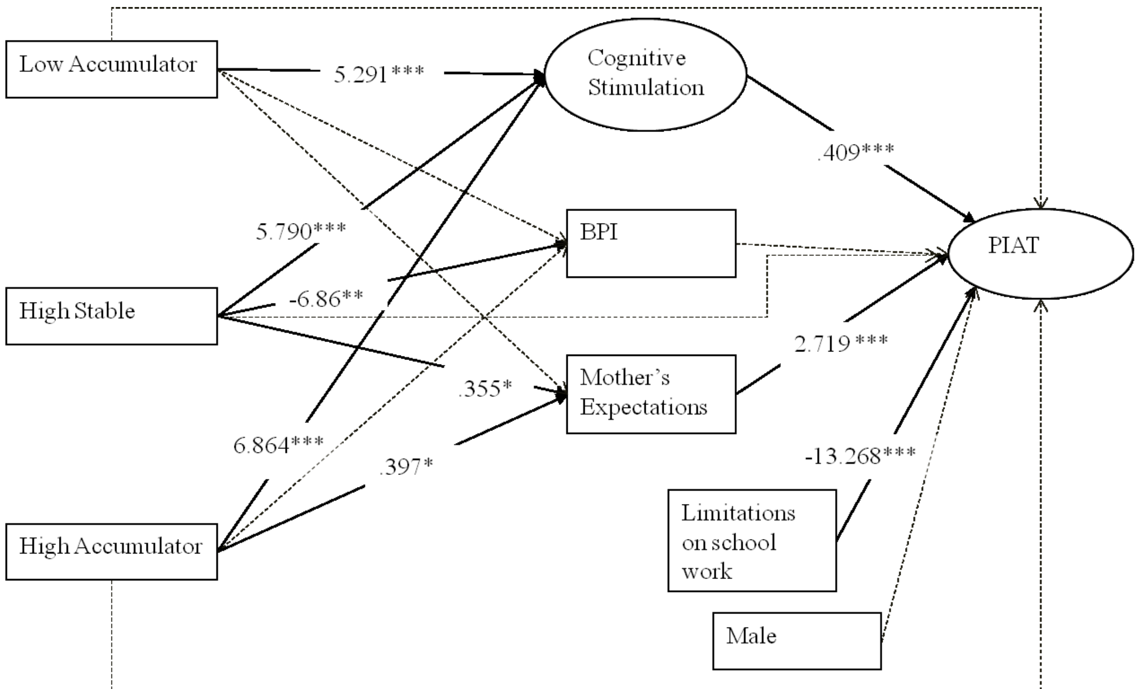

Figure 18. Mediated Pathways of Assets on PIAT Outcomes (Low Stable Class as Reference)

Note: lighter arrows represent non-significant paths
*p < .05; ** p < .01; *** p < .001

The data further indicates that children from the Low Accumulator asset trajectory class have similar levels in the quality of cognitive stimulation on the home environment as those from the High Stable and the High Accumulator asset trajectory classes. And similar to the quality of cognitive stimulation in the home environment, mothers of children from the Low Accumulator asset trajectory class had similar expectations for their children compare to the other classes (see figure 19).

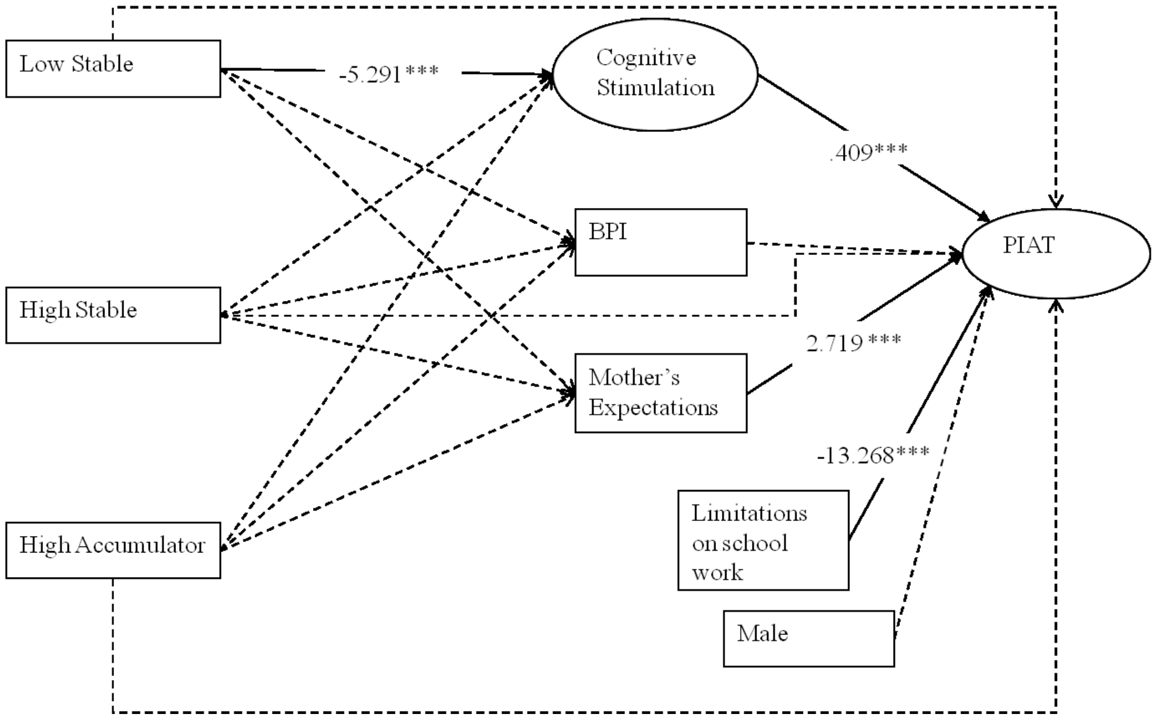

Figure 19. Mediated Pathways of Assets on PIAT Outcomes (Low Accumulator Class as Reference)

Note: lighter arrows represent non-significant paths
*** p < .001

Table 10 provides a summary of the results of the models, with the Low Stable and Low Accumulator classes as the reference group respectively.

Table 10.

Effects of Asset trajectories on the PIAT outcomes.

	LS class as reference	LA class as reference
	b (S.E.)	b (S.E.)
PIAT On		
Mother's expectation'96	2.719 (.524)***	2.719 (.524)***
Home Cognitive Stimulation	.409 (.074)***	.409 (.074)***
BPI '96	-.037 (.031)	-.037 (.031)
School Work Limitations '96	-13.268 (2.760)***	-13.268 (2.760)***
Male	1.121 (.790)	1.121 (.790)
Low Stable (LS)	-	-.072 (2.112)
Low Accumulator (LA)	.072 (2.122)	-
High Stable (HS)	1.233 (1.842)	1.181 (2.684)
High and Accumulator (HA)	1.252 (1.848)	1.162 (2.603)
Home Cognitive Stimulation On		
Low Stable (LS)	-	-5.291 (1.516)***
Low Accumulator (LA)	5.291 (1.516)***	-
High Stable (HS)	5.790 (1.028)***	.499 (1.594)
High Accumulator (HA)	6.864 (1.292)***	1.563 (1.682)
Mother's Expectation On		
Low Stable (LS)	-	-.282 (.222)
Low Accumulator (LA)	.282 (.222)	-

	LS class as reference	LA class as reference
	b (S.E.)	b (S.E.)
High Stable (HS)	.355 (.140)*	.073 (.275)
High Accumulator (HA)	.397 (.165)*	.116 (.242)
BPI On		
Low Stable (LS)	-	3.691 (3.564)
Low Accumulator (LA)	-3.619 (3.564)	-
High Stable (HS)	-6.856 (2.492)**	-3.237 (4.340)
High Accumulator (HA)	-4.238 (2.782)	-.619 (4.769)

Note : $\chi 2$ (54) = 145.76; CFI = .959; TLI = .939; RMSEA = .040;
* $p< .05$; ** $p < .01$; *** $p< .001$

To test for the robustness of the model, a separate analysis with the PIAT subtests included as separate outcomes within the same model was estimated. This model yielded the same substantive results as the original model with the PIAT subtests constructed as a single latent outcome. In this model, there are also no significant direct associations between assets and each PIAT subtest. In addition, all three subtests are significantly associated with home cognitive stimulation, though PIAT Math has the strongest relationship (b = .301, p = .000) compared to PIAT Reading Comprehension (b = .271, p = .000) and PIAT Reading Recognition (b = .279, p = .000).

All three outcomes are also significantly associated with mother's expectation at the $p < .001$ level, with PIAT Reading Recognition ($b = .212$) having the highest estimates compared to PIAT Math ($b = .207$) and PIAT Reading Comprehension ($b = .199$).

As with the PIAT Latent model, limitations on school work is associated with all three PIAT subtest while BPI is not significantly associated with any of the PIAT subtests. Gender is the only control variable that has different associations depending on PIAT subtests. It is significantly associated with PIAT Math, but not to either of the PIAT Reading subtests. All three PIAT subtests also co-vary significantly.

As the pattern of associations are the same with respect to the key predictors for the three PIAT subtests, and the assumption that all three PIAT subtests measure the underlying latent construct of academic achievement, I proceeded to use the PIAT latent for ease of interpretation. The model with PIAT outcomes constructed as a latent variable also had slightly better model fit.

Asset Trajectories and High School Graduation

As mentioned earlier, four latent asset trajectory classes were derived and identified from the data measuring net worth from 1987 to 2000. Of the classes, 78 percent of the children were assigned to the Low Stable class, 4 percent to the Low Accumulator class, 12 percent to the High Stable class, and 6 percent to the High Accumulator class. As with the PIAT outcomes, the data indicates that the proportion of children within each class graduating from high school by 2006 increases with increasing levels of assets. Where 83 percent of the children in the High Accumulator class reported having graduated from high school, only 58 percent of children from the Low Stable class reported doing so. There is also a general increasing trend for children's own educational aspirations and in the quality of cognitive stimulation at home with higher levels of assets. The weighted means of the key variables are listed in table 11. Independent samples t-tests also revealed that members of the Low Stable class have significantly lower rates of high school graduation ($t = 12.28$, $p < .001$), significantly lower level of children's educational aspirations ($t = 6.39$, $p < .001$), and significantly poorer quality of home cognitive stimulation (see table 11) for every survey year, compared to members of the other asset trajectory classes. In fact, with exception of BPI and limitation on school work, Low Stable children have significantly lower means on most of the indicators compared to non-Low Stable children.

Table 11.

Descriptives for the Early-Mid Childhood Sub-Population.

	Latent Asset Trajectory Classes			
	LS[c]	LA[c]	HS[c]	HA[c]
Outcome Measure[a]				
Graduated from High School	0.58***	0.77***	0.79***	0.83***
	(0.02)	(0.11)	(0.07)	(0.08)
Mediating Variables[b]				
Child's Educational Aspirations	3.96***	4.17*	4.11	4.31***
	(0.05)	(0.24)	(0.15)	(0.17)
Home Cognitive Stimulation'88	100.09***	105.01***	103.66**	109.13***
	(0.70)	(3.09)	(2.40)	(2.16)
Home Cognitive Stimulation'90	98.03***	104.29***	106.98***	106.64***
	(0.70)	(2.62)	(1.56)	(1.83)
Home Cognitive Stimulation'92	97.85***	107.44***	105.93***	110.32***
	(0.74)	(3.32)	(1.45)	(1.53)
Home Cognitive Stimulation'94	98.04***	106.44***	107.14***	111.17***
	(0.71)	(2.94)	(1.69)	(2.27)
Home Cognitive Stimulation'96	97.9***	104.57***	106.23***	107.95***
	(0.75)	(2.4)	(1.37)	(2.36)
Home Cognitive Stimulation'98	98.11***	107.99***	106.70***	112.40***
	(0.74)	(2.39)	(1.76)	(1.74)
Home Cognitive Stimulation'00	95.62***	102.52***	103.56***	109.95***
	(0.80)	(2.87)	(2.11)	(2.09)

	Latent Asset Trajectory Classes			
	LS[c]	LA[c]	HS[c]	HA[c]
Control Variables				
PIAT Math'96[b]	102.49***	107.93***	109.01***	107.53***
	(0.72)	(2.64)	(1.91)	(2.54)
PIAT Reading	103.97***	107.61*	111.23***	109.41***
Recognition'96[b]	(0.73)	(3.55)	(2.30)	(2.43)
PIAT Reading	101.72***	103.19	107.57***	106.09***
Comprehension'96[b]	(0.72)	(3.26)	(1.57)	(2.45)
Mother's	3.58***	3.86**	4.00***	3.94***
Expectations'96[b]	(0.04)	(0.25)	(0.16)	(0.14)
BPI'96[b]	106.72***	103.98	100.24***	101.95**
	(0.70)	(3.52)	(2.07)	(2.68)
Limitations on School	0.05*	0.08	0.03	0.00***
Work'96[a]	(0.01)	(0.07)	(0.02)	(0.00)
Male[a]	0.50 (0.02)	0.42 (0.14)	0.57* (0.07)	0.44 (0.11)
Other Background Variables[a]				
Non-black/Non-	0.73***	0.91***	0.96***	0.97***
Hispanic	(0.02)	(0.03)	(0.02)	(0.02)

	Latent Asset Trajectory Classes			
	LS[c]	LA[c]	HS[c]	HA[c]
Parents with at least Associate Degrees'00	0.40*** (0.02)	0.78*** (0.09)	0.58*** (.08)	0.81*** (0.10)

Notes: LS – Low Stable class (n = 733); LA – Low Accumulator class (n = 28); HS – High Stable class (n = 65); HA – High Accumulator class (n = 32)

[a] Weighted proportions with the mean standard error in parenthesis

[b] Weighted means with the mean standard error in parenthesis

[c] Members of each class are compared against non-members using independent sample T-tests or Chi-square tests. Significant findings are indicated where * $p < .05$, ** $p < .01$ and *** $p < .001$

In the model estimating the effects of asset trajectories on high school graduation, the outcome variable is the dichotomous variable indicating high school graduation while the predictors are the asset trajectory classes. Included as mediators are the continuous latent home cognitive stimulation variable estimated from home cognitive stimulation subtest scores collected biennially from 1988 to 2000, and the continuous variable measuring children's own educational aspirations measured in 2000. Other covariates in this model are children's gender and mother's educational expectations, children's limitations on school work, and standardized scores for BPI and the three PIAT subtests, all measured in 1996. Individual PIAT subtests are used as they provide more information compared to using the single PIAT latent variable.

The results indicate that the quality of cognitive stimulation (b = .034, p = .083), PIAT Reading Recognition standardized scores in 1996 (b = .026, p =.018), the child being male (b= -.410, p =.030) and the child's own educational aspirations (b = .221, p = .025), are significantly associated with the odds of graduating from high school. PIAT Math, PIAT Reading Comprehension, mother's educational expectations, BPI scores and limitations in school work, are not statistically associated with high school graduation. In addition, no direct association between membership in the different asset trajectories and high school graduation is found (see table 12). The results further indicate that the relationship between asset trajectories and high school graduation is fully mediated by the quality of cognitive stimulation in the home environment from birth to age 13/14, and by the child's own educational aspirations.

Table 12.

Effects of Asset trajectories on Odds of High School Graduation (Full Model)

	LS class as reference group	
	b	SE
Odds of High School Graduation On		
PIAT Math ‘96	.009	.009
PIAT Reading Comprehension ‘96	-.007	.011
PIAT Reading Recognition ‘96	.026*	.011
BPI’96	-.001	.07
Mother’s Expectations ‘96	.122	.116
Child’s Aspirations ‘00	.221*	.099
Home Cognitive Stimulation	.034#	.019
Male	-.410*	.189
Limitations on School Work ‘96	.660	.576
Low Accumulator (LA)	.508	.672
High Stable (HS)	.654	.425
High Accumulator (HA)	.781	.619
Home Cognitive Stimulation On		
Low Accumulator (LA)	5.260***	.1332
High Stable (HS)	5.452***	.900
High Accumulator (HA)	8.023***	1.026

	LS class as reference group	
	b	SE
Child's Aspirations On		
Low Accumulator (LA)	.204	.238
High Stable (HS)	.150	.159
High Accumulator (HA)	.350#	.181

Notes: AIC = 52910.605 (S.D. = 68.849); BIC = 53111.884 (S.D. = 68.849); SABIC = 52978.500 (S.D. = 68.850), N = 891;
# p < .10; * p< .05; ** p < .01; *** p< .001

As no significant direct relationship between the asset classes and the odds of high school graduations are observed, the model was re-estimated with the direct paths between the asset trajectory classes and high school graduation removed. The model information criteria for this reduced model were generally smaller or very similar to the full model, with BIC being lower at 53102.238 compared to 53111.884, and SABIC marginally lower at 52978.38 compared to 52978.500. The AIC was, however, slightly higher at 52915.337 compared to 52910.605. As the information criteria are very similar or smaller to the full model, the more parsimonious reduced model with no direct paths between asset trajectories and high school graduated is adopted (see figure 20).

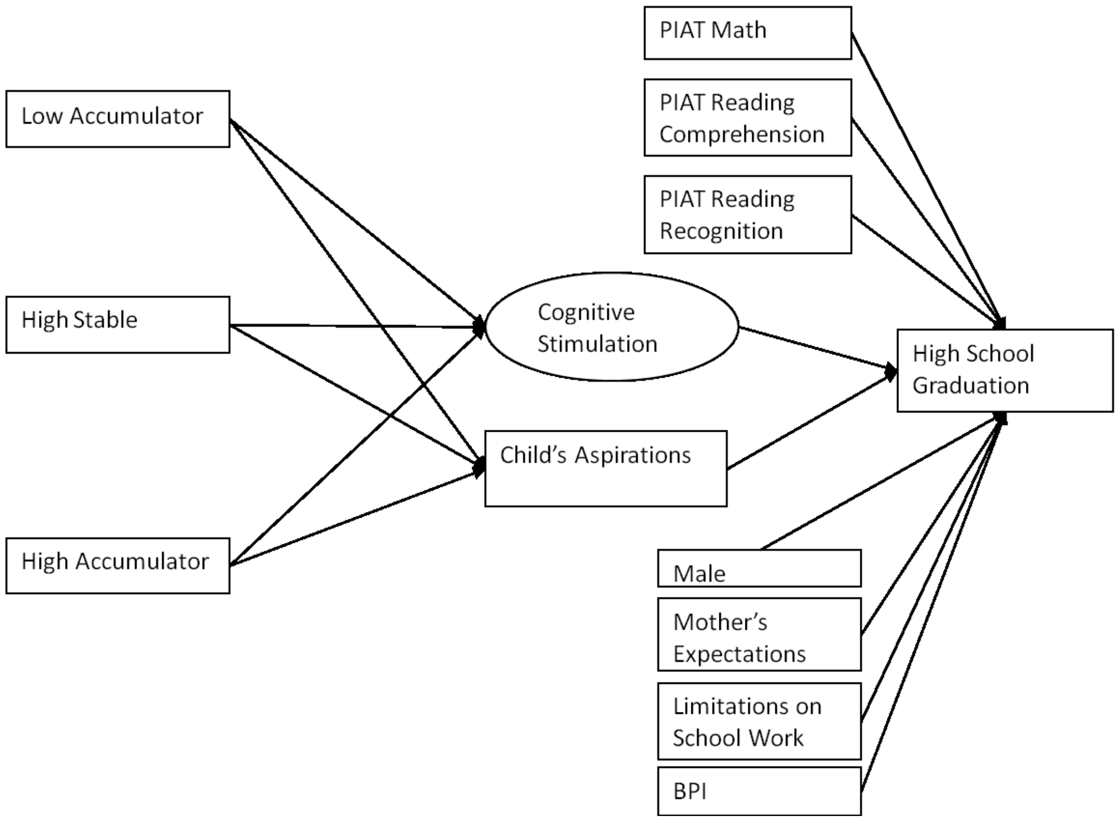

Figure 20. Reduced Model with Fully Mediated Pathways

In this model, the quality of cognitive stimulation (b = .048, p = .012), PIAT Reading Recognition standardized scores in 1996 (b = .026, p =.014), the child being male (b= -.394, p =.035), and the child's own educational aspirations (b = .215, p = .028), are all significantly associated with the odds of graduating from high school.

In addition, compared to children from the Low Stable asset trajectory class, children in the Low Accumulator (b = 5.275, p = .000), HS (b = 5.475, p = .000) and

High Accumulator (b = 8.041, p = .000) classes have significantly higher quality of cognitive stimulation in the home environment growing up. In addition, the results indicate that the higher the initial level of assets, and the higher the rate of asset growth, the higher the quality of cognitive stimulation at home (see table 13).

With regard to children's educational aspirations, the results suggest that while children from the Low Accumulator, High Stable and High Accumulator asset trajectory classes have higher aspirations for their education, the level of aspirations are not significantly different from the aspirations of children from the Low Stable asset trajectory class.

Table 13.

Effects of Asset trajectories on Odds of High School Graduation (Reduced Model)

	LS class as reference	LA class as reference
	b (S.E.)	b (S.E.)
Odds of High School Graduation On		
PIAT Math '96	.009 (.009)	.009 (.009)
PIAT Reading Comprehension'96	-.007 (.011)	-.007 (.011)
PIAT Reading Recognition'96	.026 (.011)*	.026 (.011)*
BPI'96	-.002 (.007)	-.002 (.007)
Mother's Expectations'96	.112 (.115)	.112 (.115)

	LS class as reference	LA class as reference
	b (S.E.)	b (S.E.)
Child's Aspirations'00	.215 (.098)*	.215 (.098)*
Home Cognitive Stimulation	.048 (.019)*	.048 (.019)*
Male	-.394 (.187)*	-.394 (.187)*
Limitations on School Work'96	.662 (.546)	.662 (.546)
Home Cognitive Stimulation On		
Low Stable (LS)	-	-5.254 (1.326)***
Low Accumulator (LA)	5.275 (1.332)***	-
High Stable (HS)	5.475 (0.899)***	.222 (1.475)
High Accumulator (HA)	8.041 (1.023)***	2.788 (1.517)#
Child's Aspirations On		
Low Stable (LS)		-.204 (.238)
Low Accumulator (LA)	.204 (.238)	-
High Stable (HS)	.150 (.159)	-.053 (.306)
High Accumulator (HA)	.350 (.181)#	.147 (.334)

Notes: AIC = 52915.337 (S.D. = 71.558); BIC = 53102.238 (S.D. = 71.558); SABIC = 52978.382 (S.D. = 71.558), N = 891; # p < .10; * p< .05; ** p < .01; *** p< .001

Consistent with research, the findings support the notion that assets are associated with higher odds of graduating from high school. The results further suggest that this relationship is fully mediated by the quality of cognitive stimulation in the home environment as the child is growing up. However, the results do not support previous findings that children's educational aspirations mediate the relationship between assets and high school graduation, adjusting for the other covariates in the model (see figure 21).

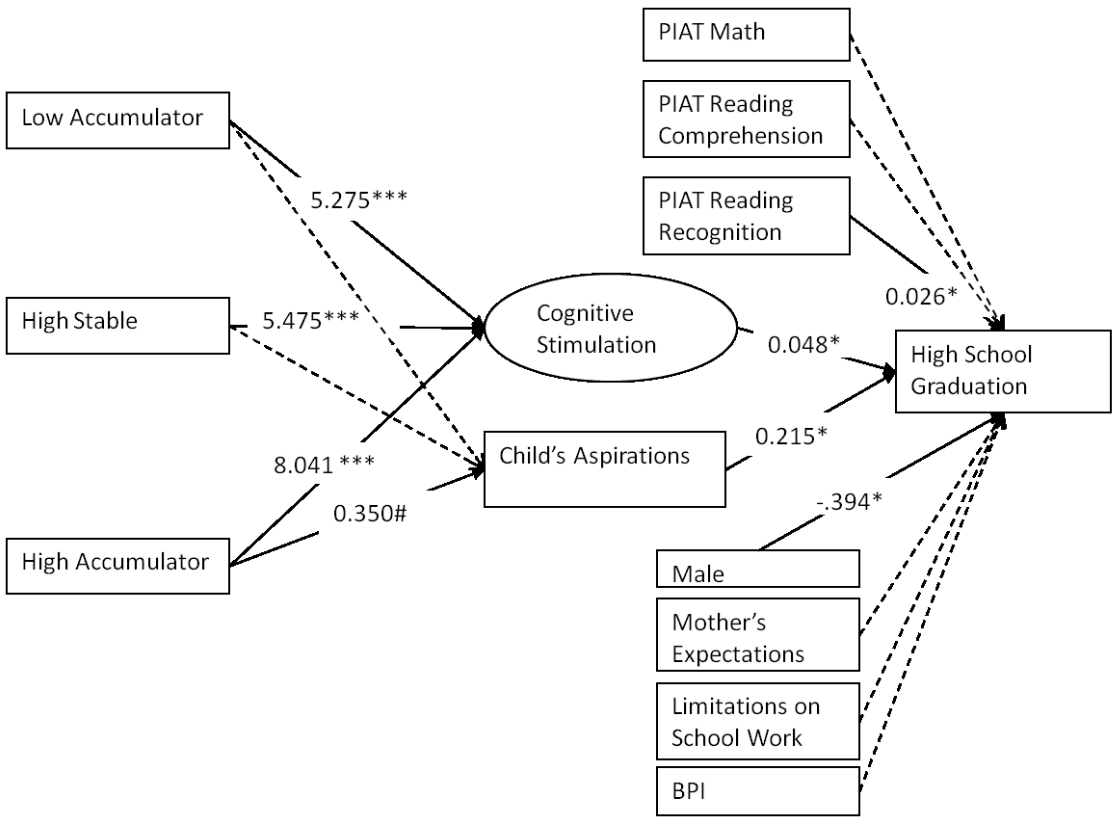

Figure 21. Effects of Asset Trajectories on High School Graduation (Low Stable Class as Reference Group)

Notes: lighter arrows represent non-significant paths

# p < .10; * p < .05; ** p < .01; *** p < .001

In addition, the results suggest that the nature of the relationship varies depending on membership in the different asset trajectory classes. Compared to children from the Low Stable asset trajectory class, children from the other asset trajectory classes have significantly higher levels of home cognitive stimulation. However, children from the Low Accumulator asset trajectory class have similar levels of cognitive home stimulation compared to children from the High Stable and High Accumulator asset trajectory classes. In terms of children's educational aspirations, there are no significant differences across the asset trajectory classes at the

$p < .05$ level (see fig 22).

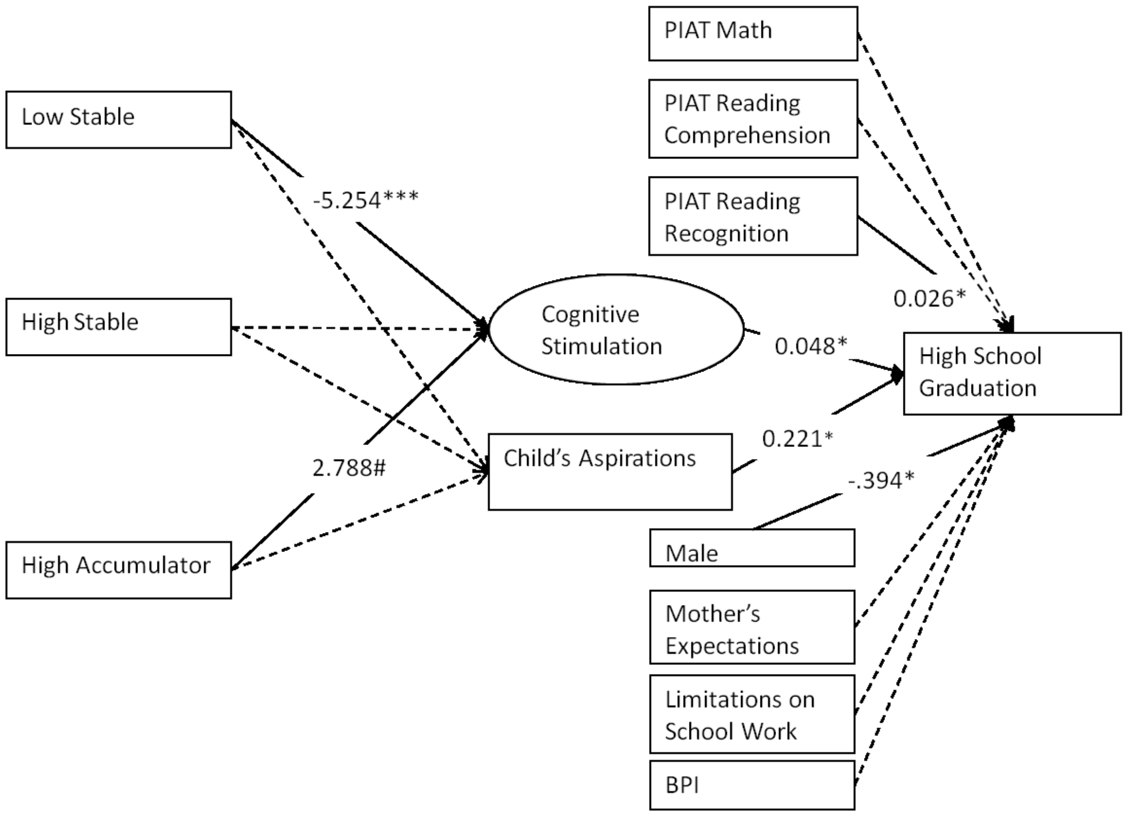

Figure 22. Effects of Asset Trajectories on High School Graduation (Low Accumulator Class as Reference Group)

Notes: lighter arrows represent non-significant paths

# p < .10; * p < .05; ** p < .01; *** p < .001

Research Aim 4: Does the Timing of Asset Accumulation Matter?

For this research aim, a two-class conditional GMM for asset accumulation is first estimated to model asset accumulation for the early childhood years from 1987 to 1993, with one class modeling a stable asset trajectory and the other modeling an increasing asset trajectory. A second two-class GMM is then estimated for the middle childhood years from 1994 to 2000, incorporating the class assignment from the first model as known classes to model the trajectories for the early childhood period (see figure 7). The result is a four-class model, with one class representing a stable asset trajectory throughout early and middle childhood (Stable class), a class representing a stable trajectory during early childhood and an increasing trajectory during middle childhood (Stable-Accumulate class), a third class representing an increasing trajectory in early childhood and a stable pattern in middle childhood (Accumulate-Stable class), and the last class representing an increasing trajectory through early and middle childhood (Accumulate class). The observed mean household net- worth values of the different asset trajectory classes are depicted in figure 23. The means of the key variables across the classes are presented in table 14.

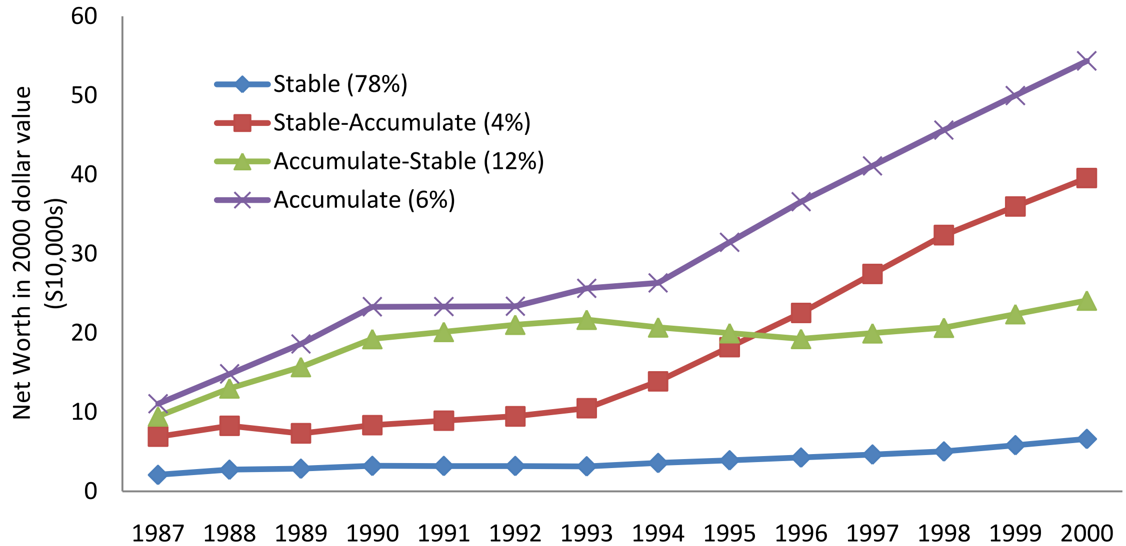

Figure 23. Asset Trajectories over Early and Middle Childhood

As can be seen from table 14, the percentage of children who graduated from high school increases as assets increase. In addition, it appears that the Accumulate-Stable (AS) class has the highest proportion of children who graduated from high school at 83 percent, while only 60 percent of children from the Stable (SS) class graduated from high school. As for the Stable-Accumulate (SA) class, 70 percent of children graduated from high school, and 77 percent of children from the Accumulator (AA) class also reported as having graduated from high school. Chi-square analyses further indicated that graduating from high school is significantly associated with class membership. More children from the Accumulate-Stable class (82.6%) graduated from high school compared to non-Accumulate-Stable class (62.25%) children ($\chi^2(1) = 207241$, $p < .001$). Significantly more children from the Stable-Accumulate class ($\chi^2(1) = 14500$, $p < .001$) and the Accumulator class ($\chi^2(1) = 40231$, $p < .001$) have high school diplomas as well, compared to children who are not in their respective classes. Significantly fewer children from the Stable class (60%), however, graduated from high school compared to children who are not in the Stable class (75%) ($\chi^2(1) = 311784$, $p < .001$).

In terms of children's own aspirations for their educational outcomes, children from the Stable-Accumulate and Accumulate-Stable classes have the highest means at 4.27 and 4.26 respectively, while Accumulator class children had mean scores of 4.16. Again, children from the Stable class have the lowest level of aspirations with a mean score of 3.96. Similar trends across the asset trajectory classes are also observed for the quality of cognitive stimulation in the home environment, and for the other control variables. Statistically, the mean aspiration levels of children in the Stable are significant different compared to children in the other classes ($t = -7.4$, $p < .001$). Children's aspirations for the Accumulator class, however, are not significantly different from children who are not in the Accumulator class ($t = 1.63$, n.s.) (see Table 14).

With regard to racial make-up of the asset trajectory classes, mothers in the Stable-Accumulate, Accumulate-Stable and Accumulator classes are overwhelmingly non-black/non-Hispanic, at 94-, 95- and 96 percent respectively. However for the Stable class, non-black/non-Hispanic mothers make up only 75 percent of the group. When comparing children in a particular class versus children who are not in that class, Chi-square analyses further indicate that the race of mothers is significantly associated with class membership across the four asset trajectory classes (see Table 14).

Table 14.

Descriptives for Sample

	Stable[c]	Stable-Accumulate[c]	Accumulate-Stable[c]	Accumulator[c]
	Mean (SE)	Mean (SE)	Mean (SE)	Mean (SE)
Outcome Variable[a]				
Graduated from High School	.60*** (.02)	0.70*** (.07)	0.83*** (.05)	0.77*** (.09)
Mediating Variables[b]				
Children's Aspirations	3.96*** (.04)	4.27*** (.13)	4.26*** (.10)	4.16 (.12)
Home Cognitive Stimulation'88	100.28*** (.67)	106.77*** (1.78)	105.60*** (1.54)	107.71*** (2.15)
Home Cognitive Stimulation'90	98.74*** (.62)	105.45*** (1.47)	105.88*** (1.33)	105.71*** (.154)
Home Cognitive Stimulation'92	98.30*** (.64)	109.77*** (1.2)	106.11*** (1.17)	111.56*** (.8)
Home Cognitive Stimulation'94	98.47*** (.65)	109.66*** (1.4)	107.69*** (1.46)	112.33*** (1.9)

	Stable[c]	Stable-Accumulate[c]	Accumulate-Stable[c]	Accumulator[c]
	Mean (SE)	Mean (SE)	Mean (SE)	Mean (SE)
Home Cognitive Stimulation'96	98.40*** (.66)	106.34*** (1.38)	106.04*** (1.3)	108.31*** (1.99)
Home Cognitive Stimulation'98	98.66*** (.66)	107.93*** (1.19)	108.71*** (1.39)	112.94*** (1.18)
Home Cognitive Stimulation'00	96.20*** (.65)	103.83*** (1.64)	104.91*** (1.48)	108.97*** (1.85)
Control Variables				
PIAT Math'96[b]	102.91*** (.66)	107.19*** (1.61)	110.39*** (1.62)	104.41 (2.12)
PIAT Reading Recognition'96[b]	104.43*** (.67)	109.23*** (2.32)	110.80*** (1.4)	107.36 (2.62)
PIAT Reading Comprehension'96[b]	102.07*** (.64)	105.86*** (1.56)	107.62*** (1.43)	103.03 (2.39)
Mother's Expectations'96[b]	3.60*** (.04)	3.93*** (.10)	3.93*** (.09)	3.96*** (.15)
BPI'96[b]	106.44*** (.62)	99.16*** (2.08)	101.94*** (1.59)	102.07* (3.08)
Limitations on School Work'96[a]	0.05*** (.01)	0.03 (.03)	0.02* (.02)	0.00*** (.00)
Male[a]	0.51 (.02)	0.51 (.08)	0.48 (.07)	0.51 (.10)

	Stable[c]	Stable-Accumulate[c]	Accumulate-Stable[c]	Accumulator[c]
	Mean (SE)	Mean (SE)	Mean (SE)	Mean (SE)
Other Background Variables[a]				
Non-black/Non-Hispanic	0.75*** (.02)	0.94*** (.02)	0.95*** (.01)	0.96*** (.02)
Parents with at least Associate Degrees'00	0.41*** (.02)	0.67*** (.08)	0.76*** (.05)	0.81*** (.08)

Notes: [a] Weighted proportions with the mean standard error in parenthesis

[b] Weighted means with the mean standard error in parenthesis

[c] Members of each class are compared against non-members using independent sample T-tests or Chi-square tests. Significant findings are indicated where * p < .05, ** p < .01 and *** p < .001

A structural equation model using the class assignments derived from the four-class model is then estimated to compare the effects of assets on the odds of high school graduation across the different asset trajectory classes, mediated by the quality of the home cognitive stimulation and child's educational aspirations, and adjusting for PIAT scores in math and reading at around third grade, gender, mother's expectations, school work limitations, and the BPI scores. As with the models from the earlier analysis, the results of this model indicate that there are no significant direct effects of the assets on high school graduation. Rather, the effects of assets are fully mediated through the quality of cognitive stimulation and potentially by children's educational aspirations.

Table 15.

Parameter Estimates of Timing SEM Model

	Stable class as reference group	
	b	SE
Odds of High School Graduation On		
PIAT Math '96	.008	.010
PIAT Reading Comprehension '96	-.007	.011
PIAT Reading Recognition '96	.026*	.011
BPI'96	-.002	.07
Mother's Expectations '96	.120	.116
Child's Aspirations '00	.215*	.100
Home Cognitive Stimulation	.039*	.019
Male	-.378*	.191
Limitations on School Work '96	.662	.540
Stable-Accumulate (SA)	.013	.504
Accumulate-Stable (AS)	.684	.546
Accumulator (AA)	.390	1.109
Home Cognitive Stimulation On		
Stable-Accumulate (SA)	6.038***	1.100
Accumulate-Stable (AS)	5.400***	1.535

	Stable class as reference group	
	b	SE
Accumulator (AA)	7.817***	1.080
Child's Aspirations On		
Stable-Accumulate (SA)	0.321	.214
Accumulate-Stable (AS)	0.312#	.172
Accumulator (AA)	0.201	.295

Notes: AIC = 52095.845 (S.D. = 52.778); BIC = 52296.458 (S.D. = 52.778); SABIC = 52163.076 (S.D. = 52.778), N = 891; # p < .10; * p< .05; ** p < .01; *** p< .001

A reduced model without the direct paths between asset trajectories and high school graduated was next estimated and evaluated against the full model with the direct paths. This reduced model yielded slightly higher AIC of 52098.288 (compared to 52095.845), but lower BIC (52284.572 compared to 52296.458) and SABIC (52160.717 compared to 52163.076) values, indicating that the models are very similar. In addition, the nature of relationships in both models is the same. As such, the more parsimonious model without the direct paths between assets and high school graduation is adopted.

In this reduced model, high school graduation is significantly predicted by the quality of cognitive stimulation in the home environment (b = .046, p = .016), and children's educational aspirations (b = .217, p = .027), controlling for other covariates in the model. Significant control variables in the model are PIAT Reading Recognition (b = .026, p = .014) and being male (b = -.375, p = .045).

In addition, children from the Stable-Accumulate (b = 6.077, p = .000), Accumulate-Stable (b = 5.477, p = .000) and Accumulator (b = 7.884, p = .000) classes have significantly higher levels of cognitive stimulation in the home environment compared to children in the Stable class. With respect to children's educational aspirations, children from the Accumulate-Stable class (b = .312, p = .07) has higher aspirations compared to children from the Stable class. However, this difference is not statistically significant. The results thus suggest that, controlling for other covariates in the model, the effect of assets on high school graduation appears to operate through the quality of cognitive stimulation in the home environment, but not through children's aspirations.

To explore whether the timing of asset accumulation matters with respect to high school graduation, children from the asset trajectory class of Accumulate-Stable where asset accumulation happens during the early childhood stage but flattens out during the middle childhood years will be compared against those from the Stable-Accumulate asset trajectory class where asset levels remain relatively stable during early childhood but experiences significant growth during the middle childhood period. Children from both classes will also be compared against children from the Stable class.

Table 16.

Timing and the Effects of Assets on High School Graduation

	SS class as reference	SA class as reference	AS class as reference
	b	b	b
Odds of High School Graduation On			
PIAT Math '96	0.008	0.008	0.008
PIAT Reading Comprehension '96	-0.007	-0.007	-0.007
PIAT Reading Recognition '96	0.026*	0.026*	0.026*
BPI'96	-0.002	-0.002	-0.002
Mother's Expectations '96	0.112	0.112	0.112
Child's Aspirations '00	0.217*	0.217*	0.217*
Home Cognitive Stimulation	0.046*	0.046*	0.046*
Male	-0.375*	-0.375*	-0.375*
Limitations on School Work '96	0.643	0.643	0.643
Home Cognitive Stimulation On			
Stable (SS)	-	-6.066***	-5.495***
Stable-Accumulate (SA)	6.077***	-	0.572
Accumulate-Stable (AS)	5.477***	-.602	-
Accumulator (AA)	7.884***	1.806	2.376

	SS class as reference	SA class as reference	AS class as reference
	b	b	b
Child's Aspirations On			
Stable (SS)	-	-.321	-0.312#
Stable-Accumulate (SA)	0.321	-	0.009
Accumulate-Stable (AS)	0.312#	-.009	-
Accumulator (AA)	0.201	-.121	-0.112

Note: AIC = 52098.288 (S.D. = 54.805); BIC = 52284.572 (S.D. = 54.805); SABIC = 52160.717 (S.D. = 54.805), N = 877; # p < .10;* p< .05; ** p < .01; *** p< .001

The results indicate that while children from both the Stable-Accumulate and Accumulate-Stable asset trajectory classes have significantly higher home cognitive stimulation compared to children from the Stable trajectory class, they are not significantly different from each other, controlling for other covariates in the model. In addition, with respect to children's educational aspiration, children from the Stable-Accumulate asset accumulation class are again not significantly different from Accumulate-Stable class children. However, children who experience asset accumulation in their early childhood years but have stable trajectories subsequently appear to have higher aspirations for their education compared to children from the Stable trajectory class, with the difference approaching statistical significance. Children from the Stable-Accumulate class, on the other hand, have statistically similar level of aspirations as their counterparts in the Stable class.

The findings suggest that in general, experiencing asset accumulation, be it during early or middle childhood, is associated with better high school graduation outcomes. In addition, this positive association between assets and educational outcomes is mediated by the quality of home cognitive stimulation. While there is no statistical difference between children who experienced asset accumulation in early childhood compared to those who experienced accumulation only during middle childhood, the results suggest that children who experience asset growth during early childhood may have better outcomes, with 83 percent of children in the Accumulate-Stable asset trajectory class graduating from high school compared to 70 percent in the Stable-Accumulate asset trajectory class.

VI Discussion

Key Findings and Implications

Asset building as a social investment and economic development strategy has garnered the interest of policy makers around the world. As of August 2009, four pieces of legislative proposals on asset building have been introduced in the 111th U.S. Congress (CFED, u.d.), and there are plans for at least half a dozen more to be introduced later in the legislative session (King, 2009). Around the world, countries such as the United Kingdom, Canada, South Korea, and Singapore already have asset-building policies in place, and many more countries on almost every continent either have proposals to implement some form of asset-building policy, or have asset-building demonstration projects running. However, much of the asset-building policies are based on thin but slowly growing empirical and theoretical evidence. While the development and progress on the asset-building policy front have been fast and furious, the same cannot be said about the developments on the theoretical and empirical fronts. Research on asset-building is still in its early stages. There is still much to be learned and developed theoretically about the patterns of wealth accumulation - what predicts them, what are their effects, what are the mechanisms for the effects, and does the timing of when wealth accumulation matter with regard to children's educational outcomes? These questions have important implications for the design and implementation of asset-building policies, especially in a fiscally demanding environment where resources are scarce and have to be carefully targeted.

The majority of studies on assets make the assumption that there is a single growth trajectory for the population. However, Sherraden (1991) suggests that there may be more than one asset trajectory. Those with no assets are likely to continue to have no assets, and are trapped in the vicious cycle of income and asset poverty. On the other hand, those with some assets will be able to generate and accumulate even more assets, and enter into a virtuous cycle of asset accumulation that results in enhanced and improved well-being. Is there indeed more than one asset accumulation trajectory, or would a single growth trajectory better represents that asset accumulation experience of the population? This is the first research aim of the study.

The results of this study support Sherraden's postulation that there is indeed more than one asset accumulation trajectory. Examining the net worth of households with young children, four distinct asset trajectory patterns are identified. The trajectories are Low Stable where household net worth is not significantly different than zero around the time when the child was born, and whose level of net worth remained relatively flat and stable with no significant increase observed over time. The vast majority of children (78 %) belong to households under this asset trajectory class. The second trajectory class, the

Low Accumulator, has a slightly higher initial level of assets compared to the Low Stable class, though still not significantly different from zero, but has a significant growth pattern over time. Only about 4 percent of children belong to households in this class. About 12 percent of children belong to the third asset trajectory class , the High Stable class, where members have initial levels of assets that are significantly higher than zero, but with non-significant asset growth trends over time. The remaining six percent of children belong to the High Accumulator asset trajectory class with significantly higher initial level of assets, and with significant growth trends over time.

A number of observations can be made about the asset trajectory classes. First, the results suggest that there is little economic mobility in terms of assets, controlling for income, marital status, employment of mothers, number of children in the household, and parents' human capital. This is consistent with other studies which similarly a lack of meaningful economic mobility, especially in terms of wealth (e.g. Jianakoplos & Menchik, 1997; Nam, 2004; Steckel & Krishnan, 1992). In this study, I find that the vast majority of households had asset trajectories that reflected non-significant growth over time, with 78-81 percent in the Low Stable class, and another 9 – 12 percent in the High Stable class. The results further indicate only a very small proportion of households were able to experience meaningful upward mobility in terms of wealth, controlling for income, maternal marital status and employment status. This is consistent with other research on wealth mobility that finds it rare for movement from the lowest quintile to a higher (Jianakoplos & Menchik, 1997). Only four percent of households, members of the Low Accumulator asset trajectory class, were observed to have increases in assets that were sufficiently large to move them from having net worth values were initially close to the Low Stable class with model estimated means that are not significantly different from zero in 1987, to having mean net worth values that are more than 1.5 times that of the High Stable class in 2000, up from being about a third of High Stable class values in 1987. In fact, by 2000, the mean net worth of Low Accumulator class members, at around $350,000, are almost at the level of the High Accumulator class.

Second, the effects of race are evident in the results. There is a large body of work documenting the importance of race as a factor in wealth accumulation. Hispanics and African American households have been consistently been found to have lower levels of wealth ownership and net worth compared to their white counterparts (Blau & Graham, 1990; Eller, 1994; Oliver & Shapiro, 1995; Wolff, 2007a, 2007b). Investment portfolios have also been found to differ across the different races. For example, African-Americans are less likely to own stocks and transaction accounts compared to other households with similar socio-economic characteristics (Chiteji & Stafford, 1999). In this study, controlling for income, maternal marital and employment status, and other covariates in the model, I find that mothers who are non-black/non-Hispanic have significantly higher odds of belonging to asset trajectory classes that have higher initial level of assets, or have significant asset growth trends, compared to belonging to the Low Stable class. In fact, while Hispanic or African-American mothers form 22 percent of the sample, they make up less than nine percent of mothers in the Low Accumulator class. For the High Stable and High Accumulator asset trajectory classes, even fewer are Hispanic or African-American, at four- and three-percent respectively. In other words, there is a racial disparity in not just asset ownership, but in the process of asset accumulation as well. Hispanic and African-American mothers not only less likely to belong to asset trajectory classes with significantly higher net worth, they are also less likely to belong to classes that experience significant growth in assets over time, thereby further perpetuating the racial inequality. To address this racial inequality and to promote a more just distribution of wealth, it is imperative that asset-building policies have design elements that specifically target, encourage and facilitate the participation of minorities.

Third, the results support existing research that suggests that family characteristics, such as the number of children in the household, are associated with the rate of wealth accumulation within families. With finite resources within the family, additional children may dilute and strain family financial resources (Oliver & Shapiro, 1995). Alternatively, it may motivate and encourage families to save and accumulate assets for their children's futures (Lupton & Smith, 2003). Analyzing data from the

NLSY79, Painter and Shafer (2007) find that the number of children in a household has a positive and significant effect on total net worth, with each additional child being associated, on average, with an increase in net worth of $3,902. However, like Keister (2005), they also find that the relationship between the number of children and net worth to be curvilinear, with a downward trend in net worth observed after three children.

In this study, I find that a higher number of children in the household is associated with membership in the High Accumulator asset trajectory class (median = 3). Low Stable, Low Accumulator and High Stable households, on the other hand, have statistically similar number of children in the household, with a median of two children in the household respectively. The design of this study, however, does not inform us as to whether it is the number of children that leads to higher net worth and accumulation rates, or that it is the higher assets and accumulation rates that enable families to have more children. Future research may consider examining not just the association between rates of increase in assets and number of children in the household, but the causal relationships as well.

The level of human capital in the family is also another important factor in influencing the rate of asset accumulation in the household. The results of this analysis indicate that families where at least one parent has an Associate degree or higher have significantly higher odds of belonging to asset trajectories reflecting significant increase over time, that is either the Low Accumulator or the High Accumulator asset trajectory classes, compared to belonging to the Low Stable class. This is true for both for the early childhood period and for the early-middle childhood years where the odds to the Low Accumulator or High Accumulator classes compared to belonging to the Low Stable class are around 6.1 and 4.7 times higher respectively. This is consistent with other research which similarly found higher educational attainment levels to be associated with higher net worth and higher rates of asset accumulation (Keister, 2008). Higher educational attainment is also associated with higher odds of belonging to households that have positive net worth, compared to having zero or negative net worth (Land & Russell, 1996). This finding further supports the important role of human capital development and education in social mobility (Morgan & Kim, 2006). It also suggests that asset-building policies for children, all of which have components to develop the human capital of children, have the potential to enhance the economic well-being of future generations, and perhaps even narrow the economic divide.

Fourth, I find tentative support for Sherraden's (1991) suggestion that low wealth families, when provided with some assets, can be on a path of further asset accumulation, leading to better outcomes and well-being. Members of the Low Accumulator and Low Stable trajectory classes both started off with model estimated mean net worth values that were not significantly different from zero, albeit Low Accumulator class members had higher observed means of around $35,000 compared to around $14,000 for the Low Stable class in 1987. However, by 2000, the observed mean net worth for the Low Accumulator class increased to around $350,000 compared to just $65,000 for Low Stable class members. While the data is drawn from a natural observation rather than from an intervention, the results suggest that assets do beget more assets. When lower wealth families are provided with some level of initial assets, in this case around $35,000, the virtuous cycle of asset accumulation and development may be initiated, resulting in further increases in asset holdings and well-being, and to improved outcomes for children. This finding lends support for asset-building policies that aim to place low income families on the path of human and asset development through helping them build and accumulate assets.

This study also aims to test the effects of different asset accumulation trajectories on children's educational outcomes, and examine whether the mediated pathways are the same across the different trajectory class. Like other research, the results indicate that assets are associated with educational outcomes (Conley, 2001; Williams Shanks, 2007), and that the effects of assets are mediated by mothers' educational expectations for their children (Elliott & Wagner, 2007; Zhan, 2006; Zhan & Sherraden, 2003) and by the quality of the home environment (Orr, 2003; Yeung & Conley, 2004). However, the study fails to find any significant mediation effects of children's educational aspirations as have been suggested by other researchers (Destin & Oyserman, 2009; Elliott, 2009). The discrepancy could be due to methodological reasons. For example, Elliott (2009) operationlized assets as the ownership of children's college savings accounts whereas this study operationalized assets in terms of asset accumulation trajectories. In addition, Elliott further found that there is a gap between what children report they aspire to attain, and what they expect to attain educationally in the PSID dataset. The NLSY79-CYA does not make a differentiation between aspirations and expectations. It is plausible that all children aspire to reach the same levels educationally; however, expectations may be different. Further research is needed to clarify and specify the role of children's educational aspirations and expectations in asset-building interventions and policies.

Unlike most studies that found direct effects of assets on children's educational outcomes, I find the effects of assets to be fully mediated, with no direct effects observed. For PIAT outcomes at around third grade, the effects of assets are fully mediated by the quality of cognitive stimulation in the home environment as the child was growing, and by mothers' expectations for their children's education. And for high school graduation, the effects of assets are fully mediated by the quality of cognitive stimulation in the home environment throughout early and middle childhood. This lack of significant direct effects of assets on children's educational outcomes once the effects of the quality of the home environment are accounted for was also observed by Campbell (2007) in her study of three groups of children spanning early to mid childhood.

Assets do change the way people think and behave (Sherraden, 1991), and in this case, it appears the effect of assets on children's educational outcomes operate through the parents by increasing parents' investments in their children through improving the quality of the home environment for stimulating the cognitive development of their children (Becker, 1991, 2002), and through increasing expectations for their children's education. However, the direct effects appear to be limited to the parents and do not extend to children's outcomes such as children's BPI scores and educational aspirations. It is plausible that the asset effects are limited to those who are directly involved in the asset experience, in this study, the parents. The asset accumulation trajectories are based on parental net worth, which children likely have little to do with. If the asset effects are limited to those who are directly involved in the asset experience, then for asset-building policies targeting children to be effective in having a direct impact on children's trajectories, it is important that children be involved somehow in the asset accumulation process. Perhaps then will children's thinking and behavior change as a result of their direct involvement in the asset experience.

Further research is therefore needed to clarify if the effects of assets can be experienced vicariously through another party, or if a direct involvement in the asset experience is necessary. As it stands now, other than having the accounts in the child's name, most asset-building policies and proposals focus primarily on engaging the adult members of the family rather than on extending the engagement to include the children themselves.

With regard to the effects of membership in the different asset accumulation classes on children's educational outcomes, consistent with other studies that found positive effects of assets on educational outcomes, I find that children from the Low Stable asset trajectory class have poorer outcomes compared to the others. These children come from households with mean net worth values that are the lowest of the four classes throughout the 13 years of observation. In addition, I find that children from the Low Accumulator class who had similar levels of initial assets, but had a significant rate of asset growth had significantly better outcomes than children from the Low Stable class. This suggests that higher initial level of asset holdings and higher rates of increase are both associated with better outcomes, albeit through the mediated pathways. This is also consistent with the findings of Loke and Sacco (2009) who similarly find children from households with higher initial level of assets and higher rates of increase to have better PIAT outcomes.

The difference in PIAT outcomes between Low Stable class children and children from the other asset trajectory classes are both statistically and practically meaningful.

While the mean scores for Low Stable class children are around half a standard deviation lower on the standardized scale compared to children from the other asset trajectory classes, many more of Low Stable class children fail to meet the expected achievement levels for their age. Using the standardized score of a hundred to indicate achievement levels that meet expectations, between 41 to almost 50 percent of Low Stable class children failed to meet expected achievement levels for the various PIAT sub tests, compared to less than 30 percent of children from the other asset trajectory classes (see appendix 4).

In addition to demonstrating that children from the Low Accumulator asset trajectory class have better outcomes than those from the Low Stable class, the data further indicates that children from the Low Accumulator class have outcomes that are statistically similar to those of the High Stable and High Accumulator asset trajectory classes. This suggests that when low income households are placed on a trajectory of asset accumulation, children from these households can have outcomes similar to those of their wealthier counterparts. This finding lends support to the premise that asset building policies can improve the outcomes and well-being of children from lower income and lower net worth families, and place them on similar developmental and educational trajectories as their wealthier counterparts.

While not directly tested in this study, the results suggest that the relationship between assets and outcomes may not be linear, and that there may be threshold and ceiling effects. If the relationship between assets and children's outcomes were linear, we would expect to see children from the Low Accumulator class having better outcomes than children from the Low Stable class, but with poorer outcomes compared to children from High Stable and High Accumulator asset trajectory classes respectively. However, the results indicate that children from the Low Accumulator class are not significantly different from the High Stable and High Accumulator classes with respect to the mediating pathways of the quality of home cognitive stimulation, mothers' expectations, and children's aspirations. It is plausible that for lower income families, either a certain level of growth in assets or a particular level of assets held is needed before the asset effects kick in as evidenced by the difference in outcomes between the Low Stable and Low Accumulator class children. It is also plausible that on the other end, increases in assets beyond a certain point yields diminishing returns, hence the lack of significant difference between the Low Accumulator and High Accumulator/High Stable classes and between the High Stable and High Accumulator classes. Determining what these threshold and ceiling effect values are, if they exist, is of critical importance in the design of asset-building policies. This is especially so in the current challenging economic and fiscal climate. Policies that fail to get families to build up their assets to the required level will be ineffectual. Likewise, it would be an exercise of poor stewardship if public funds are used to increase the assets of families above the ceiling level where the returns of such investments are diminishing or negligible.

Information is not yet available on how much assets are needed for the effects to be seen, and how much is too much, and this is an important area for future research. Nevertheless, the results of this study suggest that asset-building policies may need to ensure that participants in the policies are able to accumulate meaningful amounts of assets for the effects to be seen. In our study, the amount is around $35,000.

At present, only Singapore's Children Development Account policy, with a government contribution of up to S$24,000 per child in savings match (up to S$18,000) and cash gifts (up to S$6,000), come anywhere close to that amount. Other policies and policy proposals in the United Kingdom, United States and elsewhere have government contributions that range from the hundreds to a few thousand dollars. Is the Singapore policy over-generous, and are the other policies too limited to see any meaningful effects? This is a fruitful area for future research.

Finally, in analyzing whether experiencing asset accumulation is more effective during early childhood compared to experiencing the accumulation in middle childhood, I find that there is no difference between the two. Children who experienced accumulation in early childhood but had a stable trajectory in middle childhood (Accumulate-Stable class), and children who had stable trajectories in early childhood but experienced significant growth in middle childhood (Stable-Accumulate class), are statistically similar with respect to the quality of home cognitive stimulation which fully mediates the relationship between assets and high school graduation. Nevertheless, children from both classes had significantly better outcomes than children who had stable trajectories throughout early and middle childhood. It seems what matters most is the fact that accumulation happens, be it during early or middle childhood. Policies that help children accumulate assets from birth such as U.K.'s Child Trust Fund, or from middle childhood such as Singapore's Post Secondary Education Account (Loke & Sherraden, 2007), may be equally effective in improving children's educational outcomes.

Limitations

One of the limitations in this study is the absence of important information in the dataset that could potentially impinge on the internal validity of the study. For example, geo-coded variables such as where the households reside, where children go to school, the quality of the school, and other regional and societal contextual information are not included in the analysis. These factors may influence how much and how fast assets accumulate and how well children are likely to perform in school, and hence may confound the findings.

The presence and value of savings specifically for children, and when these accounts are opened, are not also available. Instead, household level aggregates of asset holdings are used. Hence the changes in asset levels may or may not have any specific relationship to the children in the household. Information on the movement and transformation of assets from one form to another is also lacking. Assets may have been transformed from cash to farm equipment. While the balance sheet may reflect a decrease in assets held, the net impact of the equipment purchase may have been net positive, if other assets such as farm equipment are included in the data collected.

There is also no information on expenditures on the dataset. As Paxton (2001) noted, the asset experience of spending the asset is also important in understanding the mechanisms through which the asset effect operates. For example, assets may have been drawn down to purchase education and healthcare for the children, which lead to better outcomes. However, without expenditure data, the results may lead one to erroneously conclude that a decrease in asset leads to better outcomes.

The reliance on a single measure of assets - that of household net worth, is another limitation of the analysis. The research literature suggests that different types of assets may be associated with different asset effects. For example, Nam & Huang (2009) finds differential effects of homeownership and liquid assets on educational attainment. Bynner (2001) also finds that assets gained from inheritance had no significant associations with subsequent labor market participation whereas assets in the form of investments are. Current asset-building policies for children focus mainly on increasing money or financial resources to use as young adults. Is money asset the best type of asset to promote in the policies, or should other asset types be explored as well? The current state of knowledge does not yet include information on what type of assets lead to which types of outcomes, nor does this study explore this question. To better inform asset-building policies, future research needs include different asset measures to examine what has the greatest effect, for what outcomes, for whom, and when.

Other measures used in this study could also be improved. For example, the variable on children's educational aspirations is measured by the item "how far do you think you will go in school?". Elliott (2009) suggests that children's educational aspirations are conceptually and empirically distinct from educational expectations. The NLSY-CYA survey does not distinguish between these two constructs. It is unclear how children actually perceive this question. As a consequence, it is uncertain whether children's educational expectations or aspirations are actually measured. These two constructs will have to be addressed separately in future research to increase the validity of the findings.

The variable on whether children have any conditions that limit school work is another construct that needs further specification. Currently, it covers conditions that range from physical, emotional to mental conditions. There is no information as to which type of limitations, the number of conditions, or on the severity of the condition that the child experiences. The type and severity of the conditions can have very different impacts on the ability of the child to complete his/her homework, and to engage in the educational process. The lack of specificity on the type, number and severity of the conditions limit the usefulness of this variable in the study.

Another limitation is the extent to which the findings derived from this study could approximate the asset effects. Asset-building interventions and policies are interventions, however, the data collected and analyzed in this study are from natural observations. The relationships that are found in this study may not be generalizable to relationships that exist within the context of an intervention. Future research using intervention data is needed to further add to the theoretical and empirical base of asset-building policies.

The possibility that the four asset trajectory classes that have been extracted may not be an accurate or even correct reflection of reality is another limitation of the study. While the use of growth mixture models has gained acceptance across a wide range of fields, the approach is not without criticisms. Among the strongest criticisms are those leveled by Bauer and Curran (2003a; 2003b) who argues that the classes extracted by the models may not be true and accurate reflections of the population. GMM assumes that the repeated measures are non-normal, that this non-normality is due to the existence of a finite mixture of unobserved non-identical distributions, and that once recovered, the repeated measures are conditionally normal within classes. In addition, it is assumed that the unobserved distributions have a known distributional form that is similar across the groups to be extracted. When either or both of these assumptions are violated, the number of groups may be over-extracted (Hoeksma & Kelderman, 2006). The crux of the issue is that non-normality in the data may arise from reasons other than from the reflection of group differences. Instead, it could be easily due to sample fluctuations, method effects, and even non-normal distribution in the population. Bauer and Curran (2003a) demonstrates that even mild non-normality in an otherwise homogeneous population or mild violations of the conditional normality assumption can result in over-extraction of classes. Bauer (2004) goes on to argue that our measurement instruments are typically incapable of producing observations that meet the conditional normality assumption, and therefore the usefulness of GMM for evaluating population heterogeneity is compromised.

Muthén (2003) points out that newer mixture tests, such as the Lo-Mendell-Rubin likelihood ratio test (LRM LRT), used in this study, allows for a certain degree of within-class non-normality of the outcomes when non-normal covariates are present, and is a "breakthrough for helping to select the best-fitting number of classes" (p. 371). The addition of covariates in the model can also add confidence in the extraction of classes (Hoeksma & Kelderman, 2006; Muthén, 2003; Muthén & Muthén, 2000). If classes are not statistically different with respect to the covariates that according to theory should be, then support for the model is absent.

Lastly, Hoeksma and Kelderman (2006) suggests that growth mixture models do not search for existing groups in the data, rather, they search for optimal groups that summarizes the data most parsimoniously. In other words, while four classes are extracted in my analyses, they may not represent groups that exist in the population, but optimal groups that best summarize the data. Nevertheless, Cudeck and Henly (2003) argues that there are no true models to discover, and that the purpose of a mathematical model is to summarize data, formalize the dynamics of a behavioral process, and to make predictions (p. 378). GMMs, irrespective of how close the extracted number of classes corresponds to the true number of groups that exist in the population, allows us to do just that.

A related issue is the extent small class sizes, and the findings pertaining to these classes, are valid and generalizable. The smallest classes in the various models generally comprise just over 4 percent of the sample, or around 30 members. There are presently no rules as to how small class sizes can be, and guidelines of around one to five percent of the overall sample have been suggested (K. G. Hill, White, Chung, Hawkins, & Catalano, 2000; Morin, 2009). The literature on studies using GGMM has many examples of models with small class sizes. For example, Muthén & Muthén (2000) reported on a GGMM with the smallest class size that comprises 5 percent (or 41 members) of the sample. A GMM analysis by Jackson, Sher and Wood (2000) similarly had class sizes of around 6 percent of the sample (30 members). Muthén & Muthén (2000) advised that class membership size needs to be considered in the determination of the correct number of classes, and that models are acceptable as long as classes are meaningful and class sizes are not too small for generalizations to be made. Nevertheless, the findings on this study need to be interpreted with caution due to the relatively small, albeit meaningful, class sizes.

Future Research

One of the observations from this study is that children from the Low Accumulator trajectory class have better outcomes than those from the Low Stable class, but are not significantly different from the High Stable and High Accumulator classes. This suggests that there may be a threshold and ceiling effects for assets. Whether or not there is a threshold of asset that needs to be present before the asset effect is seen is a theoretical question that still needs to be resolved. Bynner (2001) found that positive outcomes in health and employment could be seen with asset holdings of between £100 and £200, with increases in assets above this amount having relatively little impact. Zhan and Sherraden (2003) on the other hand, found that the effects of assets on children's high school graduation was seen only with parental savings of US$3,000 and above, below which, no significant asset effect was found. And if there is a threshold before which the asset effects kick in, is this value a global value across all people, social economic class and for all outcomes, or does it vary from person to person, from situation to situation, and from outcome to outcome? Difference in effects have also been noted across gender (Axinn, Duncan, & Thornton, 1997; M. S. Hill & Duncan, 1987) and age (Cairney, 2005).

A separate but related empirical and theoretical question that needs further examination and specification would be that of how much of a change in asset holding would be needed before the asset effects could be seen. Most of the small but growing body of work that examined the effects of asset looked at the amount of assets held at a given time and its association with the outcomes of interest. However, little has been done to examine if changes in assets over time are associated with changes in the areas that assets are said to affect. While the results of this study suggest that children from households that experienced significant increases in assets do have better outcomes, the magnitude of increase in assets may be higher than what could realistically be achieved through asset-building interventions. The experiences of various asset-based policies and interventions around the world have shown that the net worth of participants, especially those from lower income families, does not change dramatically, if at all, as a result of these policies or interventions. Advocates for such asset-based interventions themselves acknowledge that poor families will likely not go very far toward meeting the cost of college, homeownership or starting a business due to income constraints and to the caps on savings match (Bernstein, 2005). Changes in asset holding are modest and incremental at best. Future researchers need to examine if modest increases in assets do in fact result in better outcomes using intervention data.

Finally, while this study suggests that there are four classes for asset accumulation, and that quadratic slopes describe the trajectories better than linear slopes, it is acknowledged that the trajectories classes are descriptive rather than predictive. The classes derived through this exploratory analysis are based on a particular cohort observed over a specific period of history. As such, the findings may not be generalizable to other age cohorts or time periods. For example, the trajectories may look very different if other time periods are considered, such as from year 2000 to 2009 when there were multiple periods of recession. To develop a better understanding, and a theory, of asset accumulation, further research examining different time periods in history, different cohorts at different life stages, and across different socio-economic, cultural and geographical contexts would be required.

VII Conclusion

Asset-based welfare has provoked attention as "one of the most innovative ideas in recent public policy" (Gamble & Prabhakar, 2006, p. 107), and assets are increasingly seen as an important determinant of children's well-being and educational outcomes. Policies and programs to build the assets of children from birth are now occurring in several countries with Child Development Accounts emerging as a new social policy instrument. The potential of these asset-building policies may be promising, but long-term performance and outcomes are not yet known. To further advance the asset approach, and to inform practice and policy, there is a need for clearer theoretical and empirical specification of the mechanisms through which the asset effects operate. The development of theory and empirical support for the asset theory need to catch up with the development of asset-based policies and practice.

The strength of this study is the use of a longitudinal design that allows us examine if there are intra- and inter-individual differences in the initial levels of and rates of change in assets held over time. Most research on the asset effects have relied on cross-sectional and not on longitudinal data. The few 'longitudinal' studies that do exist are really cross-sectional temporal studies, in that they use cross-sectional data at an earlier point in time to measure the effects at a later point in time. The use of growth mixture modeling further allows us to unpack the asset experience into possession and process, and compare the effects of both, hence better inform policy and practice. In addition, it adds to the body of knowledge on the asset effects by examining the mediating mechanisms across the different asset accumulation trajectories. Finally, there is a scarcity of research examining whether there are critical time periods for the asset experience in a child's development. This study also extends the knowledge-base in this regard by examining the relative effects of experiencing asset accumulation during early childhood compared to experiencing it in middle childhood.

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Appendix 1. HOME-SF Cognitive Stimulation Sub-Scale Items

	Age Groups			
	< 3 yrs	3 – 5 yrs	6 – 9 yrs	≥ 10 yrs
How often child gets out of the house	x			
How many children's books child has	x	x	x	x
How often mother reads to child	x	x	x	
How many magazines family gets		x		
Does child have record/tape/CD player		x		
Family member helps child learn numbers		x		
Family member helps child learn alphabet		x		
Family member helps child learn colors		x		
Family member helps child learn shapes and sizes		x		
Is there a musical instrument child can use at home			x	x
Does family get a daily newspaper			x	x
How often child reads for enjoyment			x	x

	Age Groups			
	< 3 yrs	3 – 5 yrs	6 – 9 yrs	≥ 10 yrs
Does family encourage hobbies			x	x
Does child get special lessons or activities			x	x
How often mother takes child to grocery	x			
How often child is taken on an outing		x		
How often child was taken to a museum in past year		x	x	x
How often child taken to theatre in the past year			x	x
How many cuddly or role-playing toys child has	x			
How many push or pull toys child has	x			
Mother's belief about how child learns best	x			
Mom provided toys or interesting activities	x			
Child's play environment appears safe	x	x		
Home interior is dark or monotonous		x	x	x
All visible rooms are reasonably clean		x	x	x
All visible rooms are minimally cluttered		x	x	x

	Age Groups			
	< 3 yrs	3 – 5 yrs	6 – 9 yrs	≥ 10 yrs
Do parents discuss TV programs with child			x	x
Building has no structural/health hazards			x	x

Appendix 2. Items on the Behavior Problems Index

1. ANXIOUS/DEPRESSED HAS SUDDEN CHANGES IN MOOD/FEELING
2. ANXIOUS/DEPRESSED FEELS/COMPLAINS NO ONE LOVES HIM/HER
3. HEADSTRONG IS RATHER HIGH STRUNG, TENSE, NERVOUS
4. ANTISOCIAL CHEATS OR TELLS LIES
5. ANXIOUS/DEPRESSED IS TOO FEARFUL OR ANXIOUS
6. HEADSTRONG ARGUES TOO MUCH
7. HYPERACTIVE HAS DIFFICULTY CONCENTRATING/PAYING ATTENTION
8. HYPERACTIVE IS EASILY CONFUSED/IN A FOG
9. ANTISOCIAL BULLIES OR IS CRUEL/MEAN TO OTHERS
10. HEADSTRONG IS DISOBEDIENT AT HOME
11. ANTISOCIAL DOES NOT FEEL SORRY AFTER MISBEHAVING
12. PEER PROBLEMS HAS TROUBLE GETTING ALONG W/ OTHERS
13. HYPERACTIVE IS IMPULSIVE - ACTS W/OUT THINKING
14. ANXIOUS/DEPRESSED FEELS WORTHLESS OR INFERIOR
15. PEER PROBLEMS IS NOT LIKED BY OTHER CHILDREN
16. HYPERACTIVE HAS TROUBLE WITH OBSESSIONS, ETC
17. HYPERACTIVE IS RESTLESS, OVERLY ACTIVE, ETC
18. HEADSTRONG IS STUBBORN, SULLEN, OR IRRITABLE
19. HEADSTRONG HAS STRONG TEMPER, LOSES IT EASILY
20. ANXIOUS/DEPRESSED IS UNHAPPY, SAD, OR DEPRESSED
21. PEER PROBLEMS IS WITHDRAWN, NOT INVOLVED W/ OTHERS
22. ANTISOCIAL BREAKS THINGS DELIBERATELY

23. DEPENDENT CLINGS TO ADULTS
24. DEPENDENT CRIES TOO MUCH
25. DEPENDENT DEMANDS A LOT OF ATTENTION
26. DEPENDENT IS TOO DEPENDENT ON OTHERS
27. ANTISOCIAL IS DISOBEDIENT AT SCHOOL
28. ANTISOCIAL HAS TROUBLE GETTING ALONG W/TEACHERS

Appendix 3. Comparison of Weighted Means between Original and Imputed Datasets

Variable	Description	Unimputed Data				Imputed Data		
		N	Missing	Mean	SE Mean	N	Mean	SE Mean
	Mother's Characteristics							
mage	Mother's Age	923	2%	25.67	0.1	941	25.67	0.09
rhisp	Mother's Race - Hispanic	941	0%	0.08	0.01	941	0.08	0.01
rblk	Mother's Race - Black	941	0%	0.14	0.01	941	0.14	0.01
rwhite	Mother's Race - Non-Hispanic/non-black	941	0%	0.78	0.01	941	0.78	0.01
Mar_87	Mother's Marital Status '87	898	5%	0.82	0.01	941	0.81	0.02
Mar_88	Mother's Marital Status '88	899	4%	0.8	0.01	941	0.8	0.02
Mar_89	Mother's Marital Status '89	917	3%	0.81	0.01	941	0.8	0.02
Mar_90	Mother's Marital Status '90	910	3%	0.78	0.02	941	0.78	0.02
Mar_92	Mother's Marital Status '92	922	2%	0.74	0.02	941	0.74	0.02

		Unimputed Data				Imputed Data		
Variable	Description	N	Missing	Mean	SE Mean	N	Mean	SE Mean
Mar_93	Mother's Marital Status '93	928	1%	0.73	0.02	941	0.73	0.02
Mar_94	Mother's Marital Status '94	914	3%	0.72	0.02	941	0.72	0.02
Mar_96	Mother's Marital Status '96	913	3%	0.73	0.02	941	0.73	0.02
Mar_98	Mother's Marital Status '98	889	6%	0.69	0.02	941	0.68	0.02
Mar_00	Mother's Marital Status '00	858	9%	0.67	0.02	941	0.68	0.02
memp87	Mother's Employment Status '87	898	5%	0.48	0.02	941	0.49	0.02
memp88	Mother's Employment Status '88	900	4%	0.54	0.02	941	0.54	0.02
memp89	Mother's Employment Status '89	917	3%	0.52	0.02	941	0.52	0.02
memp90	Mother's Employment Status '90	910	3%	0.54	0.02	941	0.55	0.02
memp92	Mother's Employment Status '92	922	2%	0.58	0.02	941	0.58	0.02

Variable	Description	Unimputed Data N	Missing	Mean	SE Mean	Imputed Data N	Mean	SE Mean
memp93	Mother's Employment Status '93	928	1%	0.59	0.02	941	0.59	0.02
memp94	Mother's Employment Status '94	915	3%	0.63	0.02	941	0.63	0.02
memp96	Mother's Employment Status '96	913	3%	0.69	0.02	941	0.69	0.02
memp98	Mother's Employment Status '98	889	6%	0.73	0.02	941	0.73	0.02
memp00	Mother's Employment Status '00	738	22%	0.9	0.01	941	0.87	0.01
mexp96	Mother's Expectations '96	820	13%	3.68	0.04	941	3.66	0.04
	Household Characteristics							
nchild96	No. of children’96	913	3%	2.62	0.04	913	2.6	0.04
nchild00	No. of children’00	858	9%	2.48	0.05	858	2.5	0.05

Variable	Description	Unimputed Data				Imputed Data		
		N	Missing	Mean	SE Mean	N	Mean	SE Mean
tnfi87	Total Net Family Income '87 (10,000s)	747	21%	4.18	0.11	941	4.2	0.11
tnfi88	Total Net Family Income '88 (10,000s)	736	22%	4.09	0.11	941	4.1	0.11
tnfi89	Total Net Family Income '89 (10,000s)	769	18%	4.21	0.11	941	4.2	0.11
tnfi90	Total Net Family Income '90 (10,000s)	761	19%	4.23	0.11	941	4.3	0.11
tnfi92	Total Net Family Income '92 (10,000s)	776	18%	4.31	0.12	941	4.3	0.12
tnfi93	Total Net Family Income '93 (10,000s)	732	22%	4.3	0.12	941	4.4	0.12
tnfi94	Total Net Family Income '94 (10,000s)	724	23%	4.34	0.12	941	4.5	0.12
tnfi96	Total Net Family Income '96 (10,000s)	724	23%	4.82	0.15	941	4.9	0.15

		Unimputed Data				Imputed Data		
Variable	Description	N	Missing	Mean	SE Mean	N	Mean	SE Mean
tnfi98	Total Net Family Income '98 (10,000s)	715	24%	4.95	0.16	941	5.0	0.14
tnfi00	Total Net Family Income '00 (10,000s)	698	26%	5.23	0.17	941	5.2	0.15
nwt87t1	Total Family Net Worth '87 (10,000s)	841	11%	2.99	0.2	941	3.3	0.21
nwt88t1	Total Family Net Worth '88 (10,000s)	842	11%	4.36	0.3	941	4.4	0.28
nwt89t1	Total Family Net Worth '89 (10,000s)	823	13%	4.22	0.31	941	4.8	0.31
nwt90t1	Total Family Net Worth '90 (10,000s)	861	9%	5.44	0.36	941	5.6	0.35
nwt92t1	Total Family Net Worth '92 (10,000s)	875	7%	5.76	0.38	941	5.8	0.37
nwt93t1	Total Family Net Worth '93 (10,000s)	873	7%	5.6	0.33	941	5.9	0.34

Variable	Description	Unimputed Data				Imputed Data		
		N	Missing	Mean	SE Mean	N	Mean	SE Mean
nwt94t1	Total Family Net Worth '94 (10,000s)	833	11%	5.9	0.41	941	6.5	0.41
nwt96t1	Total Family Net Worth '96 (10,000s)	838	11%	7.3	0.47	941	7.6	0.45
nwt98t1	Total Family Net Worth '98 (10,000s)	805	14%	8.63	0.55	941	9.1	0.53
nwt00t1	Total Family Net Worth '00 (10,000s)	783	17%	10.77	0.66	941	11.5	0.73
hcog88	Home Cognitive Stimulation '88	830	12%	101.7	0.63	941	101.5	0.61
hcog90	Home Cognitive Stimulation '90	753	20%	99.88	0.62	941	99.9	0.63
hcog92	Home Cognitive Stimulation '92	791	16%	100.5	0.6	941	99.8	0.6
hcog94	Home Cognitive Stimulation '94	810	14%	100.6	0.63	941	100.2	0.63
hcog96	Home Cognitive Stimulation '96	762	19%	100.2	0.65	941	99.9	0.62
hcog98	Home Cognitive Stimulation '98	729	23%	100.9	0.68	941	100.4	0.64

Variable	Description	Unimputed Data N	Unimputed Data Missing	Unimputed Data Mean	Unimputed Data SE Mean	Imputed Data N	Imputed Data Mean	Imputed Data SE Mean
hcog00	Home Cognitive Stimulation '00	571	39%	98.22	0.74	941	97.8	0.65
hccol96	Parents with Associate Degrees or higher in 1996	941	0%	0.42	0.02	941	0.4	0.02
hccol00	Parents with Associate Degrees or higher in 2000	941	0%	0.43	0.02	941	0.5	0.02
	Child Characteristics							
pmath96s	PIAT Math '96	796	15%	104.4	0.63	941	103.8	0.61
precg96s	PIAT Reading Recognition '96	794	16%	106	0.64	941	105.5	0.61
pcomp96s	PIAT Reading Comprehension '96	771	18%	103.9	0.6	941	102.8	0.59
BPI96	Behavioral Problem Index	807	14%	105.2	0.64	941	105.2	0.69
cexp00	Child's Educational Aspirations '00	553	41%	4.01	0.05	941	4.02	0.04

Variable	Description	Unimputed Data				Imputed Data		
		N	Missing	Mean	SE Mean	N	Mean	SE Mean
schwrk96	Limitation in School Work 1996	854	9%	0.04	0.01	941	0.04	0.01
cmale	Child is Male	941	0%	0.51	0.02	941	0.51	0.02
hsgrad	High School Graduate	885	6%	0.64	0.02	941	0.64	0.02

Appendix 4. Percentage of Children Meeting Expectations for PIAT Sub-tests

	Asset Trajectory Classes			
	Low Stable	Low Accumulator	High Stable	High Accumulator
PIAT Math	52.53	82.98	75.60	76.07
PIAT Reading Comprehension	50.35	71.63	75.30	69.94
PIAT Reading Recognition	58.64	72.34	76.79	79.75