Three Essays on the Economics of Education and Human Capital

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Abstract

Three Essays on the Economics of Education and Human Capital

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This thesis consists of three chapters. In the first chapter, I estimate a dynamic model of schooling on two longitudinal datasets and find that the effect of relative family income on education has decreased between the early 1990's and the early 2010's. After considering a cognitive ability measure, family background variables and unobserved heterogeneity, the marginal effects of relative income on grade progression in college have become smaller for the younger cohort and the differences between the two cohorts are not statistically significant. Meanwhile, in the same period, the effect of unobserved heterogeneity in explaining the variation in educational attainment has increased significantly.

In the second chapter, I study the effect of participation in after-school activities and working while in school on high school performance in the US. Since the decision to work or participate in extracurricular activities is endogenous, several methods were used in this paper to overcome this issue. The results show that working has a detrimental impact on individuals' GPAs. Contrary to the effect of working, participating in extracurricular activities significantly improves academic performance.

In the third chapter, I estimate a dynamic factor model of the evolution of cognitive and noncognitive skills and the role of the family environment in moulding these skills in the teenage years. The results show that parental investments (both in terms of time and money) improved noncognitive skills but not cognitive skills for the 1988 cohort. The effect on cognitive skills has increased in the later cohort.

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Chapter 1

Family Income - Schooling Relationship in the US and its Evolution

1.1 Introduction

Investment in human capital is an important source of productivity growth. However, imperfections in credit markets can distort skill investment decisions and result in less than socially optimal educational attainment.

If youth from low-income families fail to acquire a good education, it will have negative consequences for economic and social mobility. If borrowing constraints prevent economically disadvantaged youth from attending post-secondary institutions, the outcomes will be inefficient. However, if the reason for low-income youth not attending university is that they are not well-qualified or they do not have a taste for school, then the existing education gaps by income are not necessarily inefficient.

Most previous studies in this area focused on the potential role of borrowing constraints in determining college attendance. Given the strong correlation between cognitive ability and family income, those researchers tried to control for ability, family income and other family background characteristics at the same time. Doing this reduces the role of family income in most studies but does not eliminate it (Cameron & Heckman, 1998, 2001; Cameron & Taber, 2004; Carneiro & Heckman, 2002). Based on data from the 1979 cohort of the National Longitudinal Study of Youth (NLSY79), these earlier studies argue that borrowing constraints have little impact on college enrollment. However, some more recent studies (Belley & Lochner, 2007) argue that the role of family income may have changed in recent years, and they study this change in the effect of ability and family income on educational attainment between the early 1980s and early 2000s.

The results generally show that the effect of relative family income (interquartile) on educational attainment has increased over the years. However, a recent paper by Belzil and Hansen (2020) shows that the effect of real family income, as opposed to relative family income, on educational attainment has decreased between the early 1980s and early 2000s.

In my paper, I estimate the model from Belzil and Hansen (2020) using data from the National Education Longitudinal Study of 1988 (NELS88) and the High School Longitudinal Study of 2009 (HSLS09). These two population-representative longitudinal datasets follow two groups of high school students through time and have information about their family background, educational attainment, standardized math test scores and some form of noncognitive measure among many others.

In this paper, contrary to Belzil and Hansen (2020) I use income quartiles as opposed to real income and study the effect of relative family income and cognitive ability on the educational attainment of two cohorts of youth, and look at their college-attending decisions. Specifically for the 2009 cohort, this decision was made after the 2008 recession.

I then take things further and estimate a cognitive factor separately, based on the model used by Belzil, Hansen, and Liu (2022), and estimate the first model with the cognitive factor as my measure of cognitive ability. The results from this estimation show that the effect of relative family income on education has not decreased between the 1990s and 2010s.

The remainder of the paper is organized as follows. The next section reviews the related literature. Section 3 describes the data; Section 4 discusses the methodology and Section 5 presents the results. Section 6 contains the conclusion.

1.2 Literature Review

Despite all the efforts to increase access to education for all socioeconomic groups, and although the return to education, especially post-secondary education, has been increasing over the decades, the gap in college enrollment and attendance between high and low-income families has widened over time.

Since the benefits of college occur in the future but the costs occur in the present, if individuals can't borrow against their future income to finance these costs, some individuals should go to college in the sense that their lifetime benefits from going to college exceed their lifetime costs, will not do so. When facing financial constraints, students from high-income families might be able to rely on parental transfers and this may cause an educational gap between this group and the group of students from lower-income families who do not have access to these transfers.

The issue of the educational gap between high and low-income families has been the subject of many research papers over the past decades. Earlier research on the impact of parental resources on children's college attendance found little evidence that after accounting for ability and family background, parental income had much effect on the probability of children's attending college (Cameron & Heckman, 1998, 2001; Cameron & Taber, 2004; Keane & Wolpin, 2001). But more recent research found that this effect has changed over time and with time, parental income has become a more important determinant of children going to college after controlling for ability (Belley & Lochner, 2007; Lochner & Monge-Naranjo, 2011).

Cameron and Heckman (1998) estimated a discrete choice model of schooling choices on five different cohorts of US males born between 1907 and 1964. They used data from the Occupation Change in a Generation (OCG) and the NLSY79 and showed that a 10 percent increase in family income has a small effect on enrollment and graduation probabilities. They show that family background and cognitive ability as measured by the AFQT scores, have more importance in the educational attainment of youth compared to their family income.

Cameron and Heckman (2001) study the determinants of college attendance and the sources of the educational gap between minorities and whites using a dynamic discrete choice model of schooling from age 15 to 24 for a sample of NLSY79. They report that the importance of short-term credit constraints in preventing college enrollment is small and it is the long-term influence of family background such as parental education that explains the correlation between college attendance and family income. They believe that family income matters in forming the ability of children and not financing their college attendance.

Other studies such as Keane and Wolpin (1997), Carneiro and Heckman (2002) and Cameron and Taber (2004) confirm these findings with different methods. Cameron and Taber (2004) use changes in direct costs and opportunity costs and test for the importance of educational borrowing constraints in four different ways: (1) instrumental variable wage regressions, (2) years of schooling regressions with interactions between college costs and various observed characteristics likely to be correlated with borrowing constraints, (3) a structural econometric model in which borrowing rates depend on observed characteristics, and (4) a structural model that allows for unobservable heterogeneity in borrowing rates. They find no evidence that borrowing constraints impede schooling progression using any of the methods.

All these studies were done using data from individuals who made their college enrollment decisions in the 1980s. But the increase in income inequality over the past few decades, plus the increase in the sticker price of four-year colleges, has created interest in not only the effect of family income on educational attainment but also the evolution of this effect over time.

Belley and Lochner (2007), by comparing NLSY79 and NLSY97, conclude that family income has become a more important factor in college enrollment decisions in the early 2000s than in the 1980s. They regress binary indicators for educational outcomes, measured at age 21, on quartile indicators as income measures, AFQT test scores and family background regressors. They found that the gap between educational outcomes of the top and bottom-income families is higher for the 1997 cohort than the 1979 cohort. Avery and Kane (2004), Bailey and Dynarski (2011) and Page and Scott-Clayton (2016) have come to the same result.

Avery and Kane (2004) mention the existence of large gaps in college-going by family income. They refer to Ellwood, Kane, et al. (2000) who show that although college entry has been growing for all groups, these gaps appear to be widening over time. Avery and Kane (2004) argue that even if the gaps in college-going by family income were not widening, the rising payoff to college since 1980 has magnified the consequences of the gap that already exists in college entry by family income.

Bailey and Dynarski (2011) describe changes over time in inequality in post-secondary education using nearly 70 years of data from the U.S. Census and the 1979 and 1997 cohorts of NLSY. They find a widening gap between children from high and low-income families in college enrollment and graduation.

Lochner and Monge-Naranjo (2011) document two facts from US data: (1) Conditional on family income, college attendance is strongly increasing in ability. This relationship holds within all narrowly defined family income groups and has persisted for decades. (2) Conditional on ability, college attendance is strongly increasing in family income (and wealth) for recent cohorts; however, this correlation was much weaker a generation ago. They develop a human capital model with borrowing constraints explicitly derived from government student loan (GSL) programs and private lending under limited commitment.

One recent study by Hotz, Wiemers, Rasmussen, and Koegel (2018) examines the effect of parental housing wealth and income on college attendance and graduation rates, quality of college attended and on the amount of financial support parents offer for college. They also examine the effect of these decisions on the future debt levels of parents and children. Although they do not study the evolution of the educational gap, using data from the PSID, especially from the 2013 Roster and Transfers Module on the amounts of parental financial support for college, they find that increases in parental income and wealth increase the probability of children attending college, due to increase in parental financial support. To solve the potential endogeneity of parental housing wealth and income, they instrument with changes in parents' local housing and labour market conditions. They also show that the effect of an increase in parental income on college attendance is larger than the effect of an increase in parental wealth. On the other hand, parental wealth increases graduation rates, while parental income does not affect college graduation.

However, some recent studies have come with different results on the evolution of educational inequality. Kinsler and Pavan (2011), investigate gaps in college quality between different income quartiles in their paper and report that the effect of family income on college quality has not changed very much over time for the average students and has even decreased for the more able students.

Chetty, Hendren, Kline, and Saez (2014) study the evolution of the intergenerational income correlation and observe that the education gap between the low and high-income families in the US has been stable over time and it has dropped for the cohort born after 1985.

Lovenheim and Reynolds (2011) estimate a multinomial Logit model of two-year and four-year enrollments on two samples of high school graduates from NLSY79 and NLSY97. They measure the effect of real income, instead of relative income by using four income groups defined from the 1997 quartiles that they interact with AFQT terciles. The authors conclude that the income gradient has not become steeper in the 1997 cohort (except for the high-ability males). But at the same time, they believe that ignoring unobserved heterogeneity may have a big impact on their results.

Belzil and Hansen (2020) estimate a dynamic model of schooling on two cohorts of the NLSY and find that, the effect of real family income on education has practically disappeared between the early 1980's and the early 2000's. Over the same period, the relative importance of unobserved heterogeneity has expanded so much that it has become the most important determinant of education. In this paper, I use their model to investigate the evolution of the effect of relative income on education through time.

1.3 Data

My analysis is based on data from two datasets, the National Education Longitudinal Study of 1988 (NELS88) and the High School Longitudinal Study of 2009 (HSLS09). The

NELS88 is a nationally representative sample of 27,394 young American men and women who were in grade 8 (13-16 years old) when they were first surveyed in 1988 while the HSLS09 consists of a nationally representative sample of 23,503 young men and women who were in grade 9 (13-17 years old) in 2009. For both cohorts, there are information on family background and income as well as on individual cognitive skills (measured by their score in a math test). Interviews were conducted in 1988, 1990, 1992, 1994 and 2000 for the first cohort and in 2009, 2012, 2013, 2016 and 2017 for the second cohort.

Because I am interested in the effect of family income on grade progression from age 16, I removed respondents who were older than 16 at the time of the first survey. In the end, I keep only respondents born between 1972 and 1975 in the NELS88 and respondents born between 1993 and 1996 in the HSLS09. My selection criteria closely resemble those used by Belzil and Hansen (2020) and others. Also, I exclude those with missing information on included observed characteristics such as family income, standardized math scores, parents' education, number of siblings, area of residence (urban vs. rural), having a single mother and race. Given that my model deals with grade progression, I also need individual transitions and enrollment status to be available. After these exclusions, I obtained samples of 8,553 individuals for the 1988 cohort and 14,125 individuals for the 2009 cohort. I use the information on family income for each individual in the year 1987 for the first cohort and 2008 for the second cohort.

In the literature, it is common to use Armed Forces Qualification Test (AFQT) scores to control for cognitive ability. There are no AFQT scores available in the two datasets used in this study. Instead, they offer scores from a math test which I use as a measure of cognitive ability in this study. There are other test scores on reading, science, and social sciences available in NELS88 but since the only test scores reported in HSLS09 are the math test scores, I use this as my measure of cognitive ability. For each individual, I measure schooling attainment by the highest grade completed by each given age and do so between ages 16 and 21.

To show the representativeness of my sample, I report a table in which the average values for some variables in the main 1988 cohort and 2009 cohort samples may be compared with the averages in my samples (in Table 1.1). Overall, my sample is quite comparable to the pre-selection samples in terms of observed characteristics. Some of the important characteristics of my two samples are found in Table 1.2 (summary statistics).

Table 1.1: Average values of some variables in NELS88 and HSLS09 and in my sample

	NELS88	1988 Cohort	HSLS09	2009 Cohort
Black	8.6%	8.5%	10.42%	8.93%
Hispanic	11.9%	11.3%	16.16%	15.75%
Male	44.0%	47.0%	50.94%	49.59%
Number of Siblings	2.3	2.2	1.68	1.58
Father's Education	14 years	14 years	14 years	14 years
Mother's Education	14 years	14 years	14 years	14 years
Rural	31.4%	33.1%	23.65%	23.47%
Math Score	36.68	37.26	35.96	42.04
Math Score Among College Attendants	38.76	40.73	42.17	45.05
Observations	12,144	8,553	23,503	14,125

To have a better picture of the relationship between education and family income, I also calculate average schooling attainments (highest grade completed by age 21) for the first, the second, the third, and the fourth income quartiles in the 1988 cohort and compare them to the corresponding quartiles in the 2009 cohort.

There are 2 main observations to be made after looking at the highest grade completed and income quartiles. First, schooling attainment has increased for all the income quartiles except quartile two in the 2009 cohort compared to the 1988 cohort. Second, the education gap between the lowest and highest income quartiles has almost stayed the same (1.69 in the 1990s versus 1.7 in the 2010s).

Information about standardized math scores is found in the second panel of Table 2. Like educational attainment, the average math score increased in 2009 compared to the 1988 cohort. As expected, the average math score of those who have attended college is greater than the average math score in the sample.

Table 1.2: Summary Statistics

	1988 Cohort	2009 Cohort
	Educational Attainment	
Highest Grade Completed	13.75	13.87
Proportion Attended College	58.65%	56.92%
Proportion Graduated from College	37.97%	40.82%
	Parental Income	
Highest grade completed by income quartile		
Quartile 1	12.90 years	12.97 years
Quartile 2	13.79 years	13.71 years
Quartile 3	14.17 years	14.34 years
Quartile 4	14.59 years	14.67 years
	Math Score 1988 / 2009	
Average	37.26	42.04
Std Dev	12.04	11.80
Average Among College Attendants	40.73	45.39
	Other Characteristics	
Male	46.53%	49.59%
Mother's Education	14 years	14 years
Father's Education	14 years	14 years
Rural	33.18%	23.47%
Number of Siblings	2.2	1.58
Black	8.50%	8.93%
Hispanic	11.32%	15.75%
Observations	8,553	14,125

Finally, the 3rd panel is devoted to family characteristics. Among observed characteristics, the number of siblings goes from 2.2 to 1.59 between 1988 and 2009. Also, the proportion of students whose school is in a rural area goes from 33% to 23%.

1.3.1 Variable Descriptions

Family Income

For both surveys, information on family income from all sources was gathered on the first year the survey was conducted. Hence, for NELS88 the variable shows family income from all sources in 1987 and for HSLS09, in 2008. I divided each sample into four income quartiles and use dummies for whether a person belongs to a certain income quartile or not as my measures of family income.

Math Score

Both the NELS88 and the HSLS09 report mathematics assessment of algebraic reasoning test scores for students. The purpose of these tests is to provide a measure of student achievement in algebra which in this study is used as a measure of their cognitive ability.

The scores used to show students' performance on the mathematics tests are based on IRT (Hambleton, Swaminathan, & Rogers, 1991). The IRT model uses patterns of correct, incorrect, and omitted responses to calculate the ability estimates that are comparable across the low-, moderate- and high-difficulty test forms. IRT scoring has several advantages over traditional scoring. First, IRT uses the overall pattern of right and wrong answers to estimate the result so it can detect the guessing factor. This means that, if answers to several easy questions are wrong, a correct answer to a difficult question is assumed to be guessed. Second, unlike in raw number-right scoring, where omitted (skipped) responses are taken as incorrect answers, IRT uses the pattern of responses to estimate the probability of correct responses for all test questions. So, unanswered items are less likely to distort scores as long as enough items have been answered right and wrong to produce a consistent pattern. Finally, IRT scoring makes it possible to compare scores from test forms of different difficulties.

School enrollment and grade attainment

In these surveys, respondents are not asked about their current school enrollment status, the highest grade they have attended (and completed), or the dates they were enrolled in school directly and continuously, so I use other information available to extract the data. For example, in the NELS88, if a student was in grade 10 in 1990, and they did not skip or repeat a grade, I assumed that they were in grade 9 in 1989.

The school enrollment state variable I use, $d^s_{i,t}$, is constructed from the data I extract on school enrollment and grade attainment in time t. Thus, $d^s_{i,t} = 1$ if the individual was enrolled in school in period t and had an increment in his grade from period t-1. If the individual was not enrolled or was enrolled but had no grade increment, $d^s_{i,t} = 0$.

I next examine to what extent the differences in cognitive ability and family income contribute to the gaps among educational attainments of individuals. Figures 1.1 to 1.4 show high school completion and college attendance rates by income quartile and cognitive ability quartile in the NELS88 and the HSLS09.

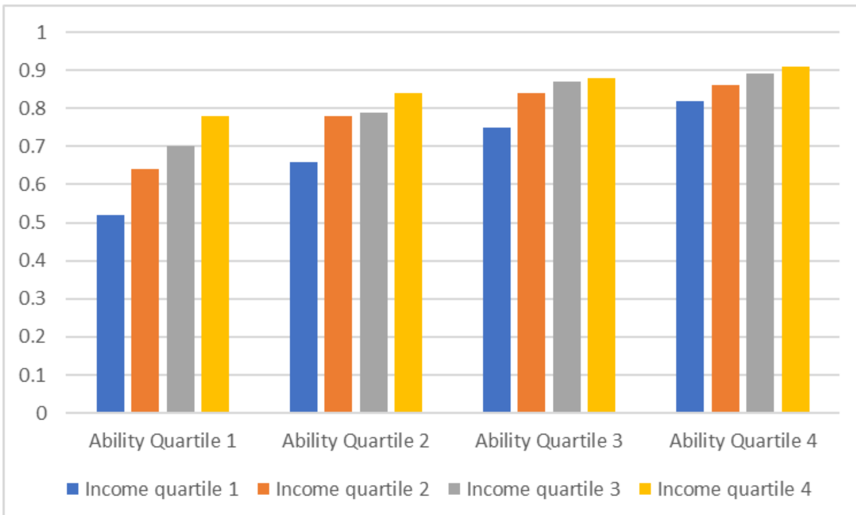

Figure 1.1: High school completion by ability and family income quartiles (NELS88)

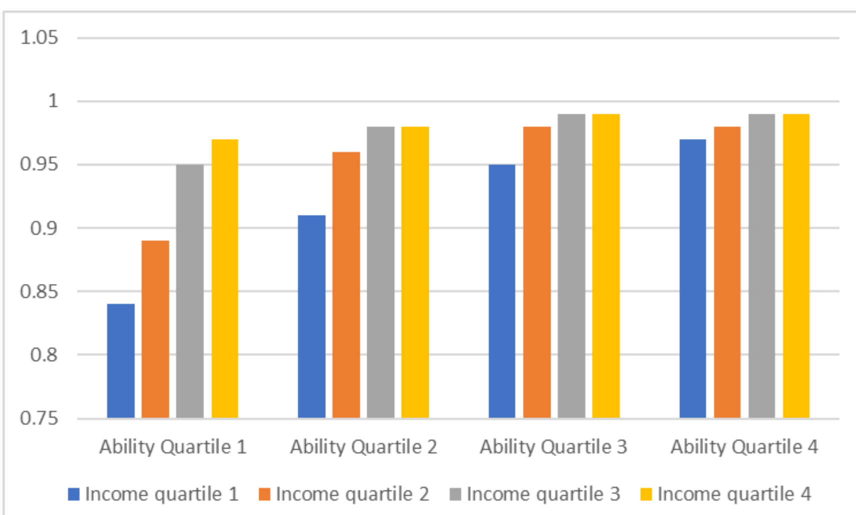

Figure 1.2: High school completion by ability and family income quartiles (HSLS09)

Figures 1.1 and 1.2 reveal the importance of ability in determining educational attainment, which is not surprising. These figures show that the rate of graduation from high school is substantially lower for individuals in the lowest ability quartile, and specifically in this group, for the individuals who are from households in the lowest family income quartile. Figures 1.1 and 1.2 show that ability has become a less important factor in determining high school completion in the younger cohort compared to the older cohort. The effect of family income at the same time, has decreased during the same period.

Figures 1.3 and 1.4 show college attendance by family income and ability quartiles. These figures show a positive correlation between college attendance and both ability and family income. The effect of family income on the college attendance decision seems to be larger for lower-ability individuals in the younger cohort, meaning that the ratio of individuals who attended college in the HSLS09 and were from the lowest ability quartile, has increased compared to their NELS88 counterparts.

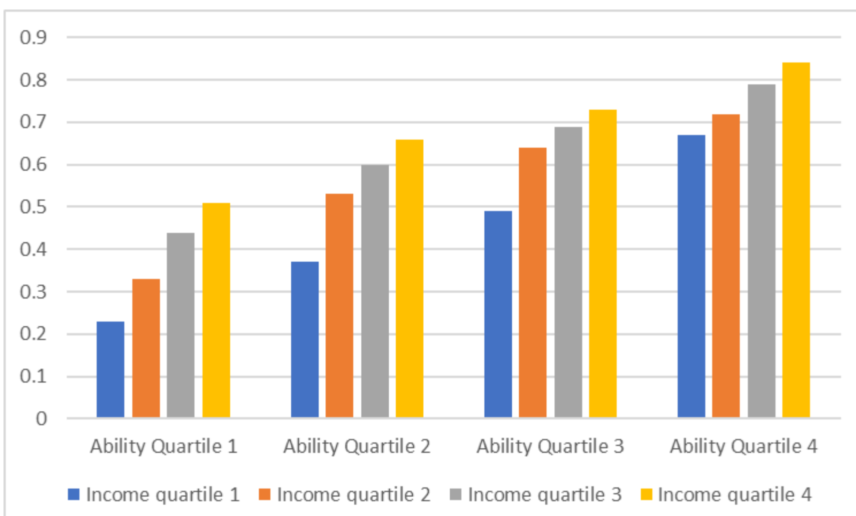

Figure 1.3: College attendance by ability and family income quartiles (NELS88)

Before introducing the model used in this paper, it is informative to evaluate the impact of family income on the highest grade completed from OLS regression. In Table 1.3, OLS estimates of the highest grade completed by age 21 on income quartiles as well as individual characteristics are reported for the two cohorts.

It can be observed from the OLS estimates that the difference between the effect of family

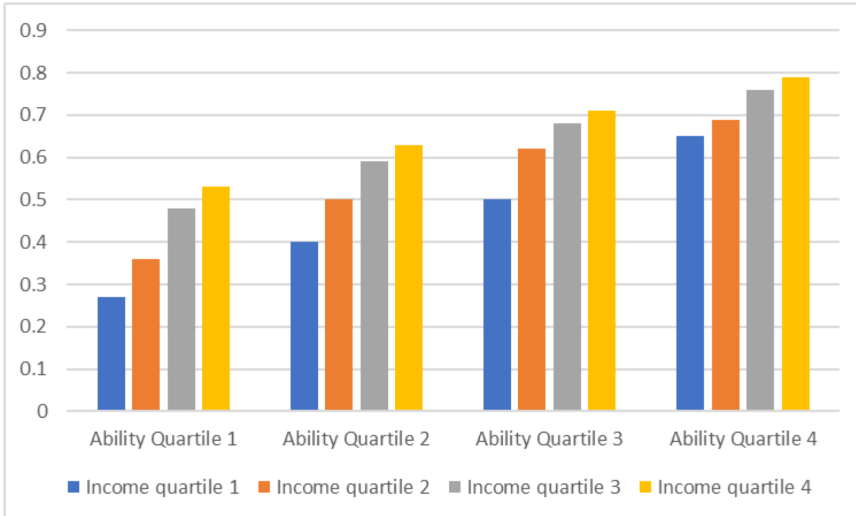

Figure 1.4: College attendance by ability and family income quartiles (HSLS09)

income on the educational attainment of youth among first and fourth-income quartiles has increased in the HSLS09 compared to the NELS88. At the same time, this difference has decreased between the first and the second and the third income quartiles.

I have also estimated another OLS regression for each cohort. A pooled OLS regression of the binary grade progression variable on family characteristics, family income quartiles and cognitive ability (measured by math test scores) quartiles. The results are presented in Table 1.4.

One can observe that the effect of relative family income on the probability of grade progression is positive and significant and the coefficients for the two cohorts are close in magnitude.

1.4 Methodology

In this paper, I use the model used by Belzil and Hansen (2020) with data from NELS88 and HSLS09 to answer the following questions:

(1) Within each cohort, do the effects of family income and the standardized test scores on grade progression differ between pre-college transitions and college transitions?

(2) How do income and standardized test scores affect educational outcomes such as grade

Table 1.3: OLS regression results with relative income

	NELS88	HSLS09
Constant	11.97**	12.34**
	(0.10)	(0.07)
Hispanic	0.07	0.03
	(0.08)	(0.05)
Black	0.58**	0.29**
	(0.09)	(0.07)
Number of Siblings	-0.14**	-0.07**
	(0.02)	(0.01)
Rural	-0.01	-0.14**
	(0.05)	(0.04)
Male	-0.12**	-0.37**
	(0.05)	(0.03)
Father's Education	0.14**	0.13**
	(0.02)	(0.01)
Mother's Education	0.09**	0.15**
	(0.02)	(0.02)
2nd Cognitive Quartile	0.83**	0.61**
	(0.08)	(0.05)
3rd Cognitive Quartile	1.33**	1.05**
	(0.08)	(0.05)
4th Cognitive Quartile	1.71**	1.38**
	(0.08)	(0.06)
2nd Income Quartile	0.41**	0.25**
	(0.07)	(0.06)
3rd Income Quartile	0.60**	0.56**
	(0.07)	(0.06)
4th Income Quartile	0.55**	0.59**
	(0.07)	(0.06)
Single Mother	-0.35**	-0.32**
	(0.07)	(0.04)
Observations	8,553	14,125

progression and college participation?

(3) How have the effects of income, test scores and unobserved heterogeneity evolved between the 1990s and 2010s?

My model is based on Belzil and Hansen's (2020) model, which following the literature

Table 1.4: Pooled OLS regression results for the probability of grade progression on relative income and relative ability

	Grade Progression Probability	
	NELS88	HSLS09
Hispanic	-0.007	-0.006
	(0.01)	(0.005)
Black	0.073**	0.034**
	(0.01)	(0.01)
Number of Siblings	-0.017**	-0.011**
	(0.001)	(0.001)
Rural	0.001	-0.016**
	(0.004)	(0.004)
Male	-0.006	-0.048**
	(0.004)	(0.002)
Mother's Education	0.020**	0.029**
	(0.001)	(0.001)
Cognitive Quartile 2	0.086**	0.070**
	(0.01)	(0.005)
Cognitive Quartile 3	0.144**	0.125**
	(0.01)	(0.005)
Cognitive Quartile 4	0.198**	0.177**
	(0.01)	(0.005)
Income Quartile 2	0.052**	0.036**
	(0.01)	(0.005)
Income Quartile 3	0.072**	0.079**
	(0.01)	(0.005)
Income Quartile 4	0.086**	0.094**
	(0.01)	(0.005)
Single Mother	-0.043**	-0.025**
	(0.01)	(0.003)
Observations	8,553	14,125

on reduced-form models of schooling, takes the intertemporal utilities to be linear (in parameters) functions.

I assume that the decision process starts at age 16. The choice variable is $d(a)$ which is equal to one when an individual decides to attend school for another year at age a and they have a grade progression, and is equal to zero otherwise.

The parameters of the model can vary with age but according to 2 different levels only.

The first level captures the effect of variables and unobserved heterogeneity on grade progression between 16 and 18 and the second one covers age 19 to 21. The schooling choice probabilities are defined as follows:

From age 16 to 18:

$$Pr(d(a) = 1|X_i, MQ_i, Q_i, G_{16}) = \Lambda(\beta_{0i}^{16} + \beta_{xi}^{16}.X_i + \beta_{MQi}^{16}.MQ_i + \beta_{Qi}^{16}.Q_i + \beta_{G_{16}i}.G_{16}).$$

From age 19 to 21:

$$Pr(d(a) = 1|X_i, MQ_i, Q_i) = \Lambda(\beta_{0i}^{19} + \beta_{xi}^{19}.X_i + \beta_{MQi}^{19}.MQ_i + \beta_{Qi}^{19}.Q_i).$$

Where:

$$\beta_{0i}^{19} = \delta_0^{19} + \delta_1^{19}.\beta_{0i}^{16}.$$

And where X_i is a vector of individual and family characteristics such as gender, parents' education, number of siblings, race, coming from an intact family and whether individual lives in a rural or urban environment, MQ_i is a vector of math score quartiles 2 to 4, Q_i is a vector of income quartiles 2 to 4, G_{16} is the highest grade completed by age 16 and $\Lambda(.)$ is the logistic distribution function.

The parameters that need to be estimated are $\beta_{0,i}^{16}$, ${\beta_x}_i^{16}$, $\beta_{MQ_{2,i}}^{16}$, $\beta_{MQ_{3,i}}^{16}$, $\beta_{MQ_{4,i}}^{16}$, $\beta_{Q_2,i}^{16}$, $\beta_{Q_3,i}^{16}$, $\beta_{Q_4,i}^{16}$ and $\beta_{G_i}^{16}$ and the age 19-21 related parameters with superscript 19.

1.4.1 Unobserved Heterogeneity

To finalize the model, I introduce unobserved heterogeneity into it. In this study, I employ the term "unobserved heterogeneity" to encompass any unmeasured factor like preferences for education, financial or non-financial education-related expenses, as well as abilities and motivations, that remain significant even after controlling for cognitive abilities and other family characteristics.

Following Bajari, Fox, and Ryan (2007), Train (2008), and Belzil and Hansen (2020), I use a fixed mass points method by covering the entire range of possible values by grid points which are chosen by first estimating the model without unobserved heterogeneity and then selecting an equal number of points above and below the estimated intercept for β^{16}_{0i}. Then I estimate all the type probabilities. I begin by taking 10 support points (the number of points and the distance between them are ad-hoc following the literature). Each type m is endowed with a vector $\beta^{16}_{0m}, \beta^{19}_{0m}$. The probability of belonging to one of the 10 types is given by multinomial logistic regressions which will be jointly estimated with the model coefficients:

$$p_m = \frac{exp(\tilde{p}_m)}{1 + \sum_{j=2}^{M} exp(\tilde{p}_j)}$$

.

The probabilities will be identified by having persistent results from repeated estimates in several periods.

1.4.2 Likelihood Function

I will estimate the model by maximum likelihood. Each individual's grade progression history is contained in the following vector:

$$\{G(16), d_i(a = 16), d_i(a = 17), ..., d_i(a = 21)\}.$$

The likelihood function for observation i is:

$$L_i(.) = \sum_{m=1}^{10} p_m. \prod_{a=16}^{T} (Pr(d_{ia} = 1|type\, m))^{I(d_{ia}=1)}.(Pr(d_{ia} = 0|type\, m))^{I(d_{ia}=0)}.$$

Where I(.) is the identity function and T is the number of periods the individual is observed in the sample. The likelihood of the sample data will be formed by the product of each contribution.

1.4.3 Latent Factor Model

Next, following the more recent literature on the estimation of schooling models (see Carneiro, Hansen, & Heckman, 2003; Heckman, Humphries, & Veramendi, 2016; Prada & Urzúa, 2017) in which the distribution of skills is obtained through latent factor estimation techniques, I estimate the distribution of the cognitive skill through factor estimation methods.

I write the cognitive factor as the sum of a component assumed to depend on a vector of observed characteristics (denoted X_i) and an orthogonal component denoted $\tilde{C}_i$.

$$C_i = C_x.X_i + \tilde{C}_i.$$

Where C_x is a vector of parameters measuring the correlation between factors and observed regressors.

Denote the j^{th} cognitive measure of individual i by $M_{i,j}$, then I will have:

$$M_{i,j} = m_{0j} + m_{cj}.C_i + \epsilon_{i,j}^{cm}.$$

where j=1,...,4 for the 1988 cohort and j=1,2 for the 2009 cohort.

The parameters m_{0j} are intercept terms affecting the location of each measure, m_{cj} are loading parameters and $\epsilon_{i,j}^{cm}$ is a measurement error shock which follows a Normal distribution with mean 0 and standard deviation σ_j^{cm}.

I use the four test results in math, reading, science and social sciences, in 1988 as measures of cognitive ability for the individuals in the 1988 cohort and the math test score in 2009 and the grade they obtained in math in grade 8 (in 2008) as measures of cognitive ability for the individuals in the 2009 cohort.

When estimating the model, I use a discrete approximation of the joint factor distribution, as I did for the unobserved heterogeneity part. I assume, in line with Bajari et al. (2007) and Train (2008), a fixed mass point approach by choosing grid points covering the entire range of possible values and estimating all the type probabilities.

To proceed, I normalize the measurements to help set up support points for the distribution of each factor. I then assume that the orthogonal part of each factor can take one of 26 values between -2.3 and 1.5 with 0.2 increments, for the NELS88. For HSLS09 the 20 mass points are spread between -2.8 and 1 with 0.2 increments. My task is to estimate the probabilities of all possible combinations. The probability of a given realization is denoted as *pr* and each *pr* is estimated as a logistic regression.

In this step, I first estimate the probabilities of each type, using the logistic regressions jointly with the variance and location and loading of the factors. I then use the expected values of the factors for each person, their unobserved heterogeneity terms in the forms of mass points and their probabilities in the model presented previously, as my measure of cognitive ability and re-estimate the model using this new information. I define the unobserved heterogeneity in the main model the same as before.

1.5 Estimation Results

To estimate the model, I defined the heterogeneity distribution over ten fixed points that range from 0.4 to 1.4 with intervals of 0.1 for both the NELS88 and the HSLS09.

As is the case for most non-linear models, the parameter estimates are not informative in themselves. For this reason, here I present the marginal effects calculated separately and present the original parameter estimates in Tables A1 and A2 in the Appendix. Since the model allows for the effect of income and standardized math test scores to change when individuals reach 19, I first calculate the income and math score marginal effects on the probability of attaining an additional grade level between 16-18 years old and then between 19 to 21 years old.

I estimated my model by a set of quartile indicators to find estimates of the evolution of educational differences which would be more comparable with the literature (specifically the results from Belley and Lochner (2007)). When estimating the model, I use the first quartile as the reference group and calculate marginal effects as the difference in probability of grade progression between a given quartile and the first one. The estimates are presented in Table 1.5.

Table 1.5: Marginal Effects for the model with income quartiles

	NELS88	HSLS09
Between age 16-18	M.E.	M.E.
Cognitive Quartile 2	0.051**	0.041**
	(9.10)	(8.94)
	[0.040,0.062]	[0.032,0.050]
Cognitive Quartile 3	0.085**	0.077**
	(14.03)	(15.66)
	[0.073,0.097]	[0.067,0.087]
Cognitive Quartile 4	0.106**	0.119**
	(15.79)	(18.68)
	[0.093,0.119]	[0.106,0.132]
Income Quartile 2	0.031**	0.029**
	(4.86)	(7.15)
	[0.018,0.043]	[0.021,0.038]
Income Quartile 3	0.045**	0.060**
	(6.65)	(10.63)
	[0.032,0.058]	[0.049,0.072]
Income Quartile 4	0.053**	0.085**
	(6.27)	(13.95)
	[0.036,0.070]	[0.073,0.097]
Between age 19-21	M.E.	M.E.
Cognitive Quartile 2	0.136**	0.068**
	(9.68)	(11.76)
	[0.108,0.164]	[0.048,0.088]
Cognitive Quartile 3	0.287**	0.147**
	(18.68)	(21.17)
	[0.257,0.317]	[0.123,0.172]
Cognitive Quartile 4	0.534**	0.258**
	(25.23)	(25.32)
	[0.493,0.575]	[0.223,0.294]
Income Quartile 2	0.108**	0.031**
	(6.94)	(4.30)
	[0.077,0.138]	[0.006,0.055]
Income Quartile 3	0.148**	0.091**
	(9.16)	(11.57)
	[0.116,0.180]	[0.064,0.106]
Income Quartile 4	0.227**	0.136**
	(11.62)	(13.88)
	[0.189,0.265]	[0.102,0.170]

1.5.1 The effects of relative family income and math scores on grade progression

To calculate the marginal effects, I calculated the marginal effect of each of these variables for each individual for each 10 types and then took a weighted average, using the estimated type proportions as weights. I then took the average over the sample.

The calculated results in Table 1.5 show that there is a large relative income effect in the 1988 cohort for the probability of grade progression (between the ages 19 and 21), which has decreased for the 2009 cohort during these ages (college years), for all three higher quartiles relative to quartile one. The relative effects between ages 16 to 18 (high school years) are smaller but show a small increase for quartiles three and four relative to quartile one in 2009 compared to 1988. However, when I estimate the 5 percent confidence intervals for these coefficients I find that these differences are mostly not significant during high school. The only significant difference is between the coefficients of the family income quartile four relative to quartile one, during high school. The effect of relative income during college has, however, significantly decreased between the 1990s and 2010s. So basically, based on this model, the effect of relative family income on the probability of grade progression has not changed between the 1990s and 2010s after controlling for other background characteristics.

As for the effect of cognitive ability, the effect doesn't show any significant difference between the two cohorts, during high school. However, cognitive ability shows a much larger effect during college and specifically, it shows a steeper gradient in 1988 compared to the 2009 cohort. The relative effect of cognitive ability during college has decreased significantly between the 1990s and 2010s.

Next, I present the marginal effects of re-estimating the model with the cognitive factor as my measure of cognitive ability. The estimated coefficients as well as the probability of each cognitive type are presented in Tables A3 and A4 in the appendix.

These new results, especially after calculating the confidence intervals for each marginal effect, show that the effect of relative family income on education has decreased or has not changed between the 1990s and 2010s. These results are in line with Belzil and Hansen

Table 1.6: Marginal Effects for the model with cognitive factor

	NELS88	HSLS09
Between age 16-18	M.E.	M.E.
Cognitive Factor	0.188**	0.116**
	(30.32)	(44.13)
	[0.176,0.200]	[0.111,0.121]
Income Quartile 2	0.050**	0.042**
	(6.48)	(6.91)
	[0.035,0.066]	[0.030,0.053]
Income Quartile 3	0.066**	0.078**
	(7.70)	(9.16)
	[0.049,0.083]	[0.061,0.095]
Income Quartile 4	0.086**	0.112**
	(9.36)	(12.55)
	[0.068,0.104]	[0.095,0.130]
Between age 19-21	M.E.	M.E.
Cognitive Factor	0.434**	0.321**
	(34.87)	(41.14)
	[0.410,0.459]	[0.306,0.337]
Income Quartile 2	0.078**	0.071**
	(6.25)	(5.39)
	[0.047,0.109]	[0.045,0.097]
Income Quartile 3	0.0106**	0.134**
	(11.23)	(7.13)
	[0.073,0.140]	[0.097,0.171]
Income Quartile 4	0.195**	0.188**
	(34.87)	(11.25)
	[0.161,0.229]	[0.155,0.221]

(2020) show that income effects on educational attainments have lost a large portion of their impact between the 1980s and 2000s. The difference between my paper and the paper mentioned above is that they look at the effect of real income as opposed to relative income.

Next, I re-estimate the model with cognitive factor, adding interactions of cognitive factor and income quartiles to see the effect of cognitive factor on the probability of grade progression for individuals in different income quartiles. The results are presented in Table 1.7. The marginal effect of the cognitive factor shows the effect of the cognitive factor on the probability of grade progression for individuals in income quartile 1. The interaction terms between the cognitive factor and each of the three income quartiles show the effect of cognitive ability on the probability of grade progression in each of the 3 higher-income quartiles. So for example, one standard deviation increase in cognitive ability in 1988, increased the probability of grade progression by 0.15 for people in the lowest income quartile.

And the interaction term between cognitive factor and income quartile 2 then shows that one standard deviation increase in cognitive ability, increased the probability of grade progression in high school for individuals in income quartile 2 by 0.22 in 1988. The estimated coefficients in high school are close for the interaction terms for quartiles 2 to 4 and looking at their estimated confidence, one can conclude they are not statistically different.

The effect of cognitive ability on the probability of grade progression in college is higher than the effect in high school. And again, the effect for people in higher income quartiles is higher than quartile 1.

When comparing the results for the 2009 cohort with the 1988 cohort, the effect has decreased except for the quartile 1 in college which has stayed the same, based on the 95% confidence intervals.

As for the effect of income on educational attainment, it has a positive effect on the probability of grade progression. However, the effect has become smaller between the early 1990s and early 2010s and the decrease is statistically significant, except for income quartile 4 compared to income quartile 1 in high school, and income quartile 3 compared to income quartile 1 in college.

The last set of results are income effects for the highest and lowest ability quartiles. The marginal effects that are presented in Table 1.7 are calculated at cognitive ability equal to zero. In Table 1.8, I present marginal effects for relative family income for the average individual in cognitive ability quartiles 4 and 1. For the high-ability individuals, as can be observed, the income effect during high school has become smaller for individuals in quartiles 2 and 3 relative to quartile 1. The effect for the individuals in this ability quartile and in income quartile 4 has not changed between the 1990s and 2010s. At the same time, the income effect for individuals in the lowest ability quartile has increased for individuals in income quartile 4 during high school. This effect has not changed for individuals with low ability and in income quartiles 3 and 2.

During college, the income effect is larger, for higher-ability individuals, compared to high school and the effect has decreased for income quartiles 2 and 4 between the 1990s and 2010s. For the lowest-ability people on the other hand, the income effect is the same during high school and college in the 1988 cohort, and the effect has increased for low-ability high-income individuals during college in the 2009 cohort compared to the 1988 cohort.

To understand the sources of changes in the marginal effects of family income and cognitive ability, it is necessary to look at the relative importance of unobserved heterogeneity within each cohort and its evolution.

1.5.2 The importance of unobserved heterogeneity

The distribution of unobserved heterogeneity can be viewed in Table A.2. In both cohorts, I find evidence of six distinct types. I answer the following question: to what extent did the relative importance of unobserved heterogeneity change between the early 1990s and the early 2010s?

To answer these questions, I simulate the distribution of unobserved heterogeneity using draws from a uniform distribution and values for the type proportions and then I run regressions of simulated highest grade completed (as measured by age 21) on individual characteristics as well as on unobserved heterogeneity and report their R-squared in Table 1.9. I also estimate regressions of simulated probabilities of grade progression during high school and college on background characteristics and unobserved heterogeneity. These results are presented in Table 1.9 as well.

From the two first columns of Table 1.9 one can observe that between the 1990s and 2010s, the explanatory power of family income and cognitive ability on educational attainment have decreased but during the same period, unobserved heterogeneity has become a stronger explaining factor of highest grade completed by individuals. Also, the unobserved heterogeneity among the rest of the variables explains the largest part of the variation in the highest grade completed by age 21 in both cohorts. These results are in line with the findings of Belzil and Hansen (2020).

Columns 3 and 4 of the table show the explanatory power of the same observed characteristics and unobserved heterogeneity on the simulated probabilities of grade progression during high school. The results show that during high school, family income explains a large proportion of variation in the probability of grade progression, and this effect has increased between the 1990s and the 2010s. In the same period, the explanatory power of cognitive ability has shrunk significantly, from 45% to 36%. Unobserved heterogeneity during high school explained 15% and 22% of the variation in grade progression probability in the 1990s and 2010s respectively. These results show that the effect of unobserved heterogeneity on grade progression has increased over 20 years, however, the impact of family income and cognitive ability is still larger during high school.

The most striking results are the impact of unobserved heterogeneity on grade progression probability during college. These results which are presented in columns 5 and 6 of Table 1.9 show that the impact of family income and cognitive ability on the probability of grade progression during college are much smaller compared to their impact in high school. At the same time, more than 70 percent of the variation in grade progression probability during college can be explained by unobserved heterogeneity and this has increased by around 8 percentage points between the 1990s and 2010s.

1.6 Interpretation and Conclusion

In this paper, I have provided evidence which shows that the effect of relative family income on education attainment has decreased between the early 1990s and early 2010s. I use data from two surveys, NELS88 and HSLS09, which are two sets of longitudinal data on educational attainments and individual and family characteristics of two groups of American youth in high school and college from 1988 to 2000 and from 2009 to 2016. I use the model from Belzil and Hansen (2020) to estimate the marginal effects of relative family income and an individual's relative cognitive ability on grade progression probabilities.

My results, in line with Belzil and Hansen (2020), show that the effect of relative family income on the probability of grade transition has decreased in a period of 21 years from

1988 to 2009. My results also show that the effect of cognitive ability, to the extent that is measured by the math test scores, has decreased during this period. This means that individuals with lower cognitive ability can transition through school more easily than 20 to 30 years ago.

These findings are in line with the evolution of college attendance in the US. The number of college enrollments has been around 20 million per year in the past years, which is larger than in the early 1990s. Coupled with the increased capacity at lower quality and lower tuition institutions, it can explain the decreasing impact of family income and cognitive ability on educational attainment.

Another finding of this paper is that the effect of unobserved heterogeneity on the probability of grade progression has increased from the 1990s to 2010s, to the extent that in college, it explains around 80 percent of the variation in this probability in the sample. This means that in more recent decades, factors such as noncognitive skills, taste for schooling and the cost of schooling (both monetary and non-monetary) which can not be controlled for by observed family background characteristics, family income and cognitive ability, explain more of a variation in this probability.

Table 1.7: Marginal Effects for the model with cognitive factor and its interactions with income quartiles

	NELS88	HSLS09
Between age 16-18	M.E.	M.E.
Cognitive Factor	0.150**	0.122**
	(19.49)	(26.34)
	[0.135,0.165]	[0.113,0.131]
Income Quartile 2	0.092**	0.033**
	(8.96)	(5.11)
	[0.072,0.113]	[0.020,0.045]
Income Quartile 3	0.128**	0.066**
	(8.30)	(7.85)
	[0.098, 0.158]	[0.049,0.082]
Income Quartile 4	0.130**	0.105**
	(8.29)	(9.76)
	[0.099,0.161]	[0.084,0.127]
Cog Factor x Income Quartile 2	0.220**	0.106**
	(20.10)	(23.74)
	[0.199,0.242]	[0.098,0.115]
Cog Factor x Income Quartile 3	0.248**	0.114**
	(18.51)	(20.84)
	[0.221,0.274]	[0.104,0.125]
Cog Factor x Income Quartile 4	0.229**	0.113**
	(14.16)	(21.40)
	[0.197,0.261]	[0.103,0.124]
Between age 19-21	M.E.	M.E.
Cognitive Factor	0.344**	0.290**
	(19.20)	(24.68)
	[0.309,0.379]	[0.267,0.313]
Income Quartile 2	0.119**	0.051**
	(7.36)	(4.05)
	[0.087,0.150]	[0.025,0.078]
Income Quartile 3	0.162**	0.110**
	(9.51)	(6.97)
	[0.129,0.196]	[0.081,0.144]
Income Quartile 4	0.288**	0.170**
	(10.06)	(10.13)
	[0.232,0.344]	[0.139,0.205]
Cog Factor x Income Quartile 2	0.428**	0.351**
	(20.19)	(28.03)
	[0.386,0.469]	[0.326,0.375]
Cog Factor x Income Quartile 3	0.451**	0.333**
	(22.14)	(10.30)
	[0.411,0.491]	[0.270,0.397]
Cog Factor x Income Quartile 4	0.570**	0.400**
	(16.62)	(21.84)
	[0.503,0.638]	[0.364,0.436]

Table 1.8: Income Effects at different values of the cognitive factor

	NELS88	HSLS09
Between age 16-18	M.E.	M.E.
Income Quartile 2 for high ability	0.117**	0.024**
	(9.15)	(3.37)
	[0.092,0.142]	[0.008,0.041]
Income Quartile 3 for high ability	0.119**	0.057**
	(8.29)	(6.16)
	[0.091,0.147]	[0.035,0.079]
Income Quartile 4 for high ability	0.124**	0.112**
	(7.56)	(8.88)
	[0.092,0.161]	[0.087,0.137]
Income Quartile 2 for low ability	0.062**	0.043**
	(8.65)	(6.14)
	[0.048,0.076]	[0.029,0.057]
Income Quartile 3 for low ability	0.052**	0.078**
	(8.51)	(8.58)
	[0.040,0.064]	[0.060,0.096]
Income Quartile 4 for low ability	0.060**	0.116**
	(9.24)	(10.73)
	[0.047,0.073]	[0.095,0.137]
Between age 19-21	M.E.	M.E.
Income Quartile 2 for high ability	0.148**	0.074**
	(7.83)	(5.70)
	[0.111,0.185]	[0.049,0.099]
Income Quartile 3 for high ability	0.162**	0.171**
	(10.25)	(8.07)
	[0.131,0.193]	[0.130,0.213]
Income Quartile 4 for high ability	0.322**	0.211**
	(8.90)	(12.59)
	[0.251,0.393]	[0.178,0.244]
Income Quartile 2 for low ability	0.087**	0.043**
	(4.24)	(2.69)
	[0.047,0.127]	[0.012,0.075]
Income Quartile 3 for low ability	0.049**	0.091**
	(6.86)	(4.12)
	[0.035,0.063]	[0.048,0.135]
Income Quartile 4 for low ability	0.084**	0.153**
	(9.12)	(6.23)
	[0.066,0.102]	[0.105,0.202]

Table 1.9: R^2 from regressions of highest grade completed and grade progression probabilities in high school and college

	HGC		PGPHS		PGPCOL	
	NELS88	HSLS09	NELS88	HSLS09	NELS88	HSLS09
Hispanic	0.0065	0.0097	0.0651	0.0385	0.0040	0.0069
Black	0.0022	0.0018	0.0024	0.0061	0.0009	0.0008
Number of Siblings	0.0190	0.0105	0.1009	0.1111	0.0221	0.0060
Rural	0.0060	0.0038	0.0000	0.0062	0.0066	0.0034
Male	0.0013	0.0060	0.0091	0.0230	0.0000	0.0017
Mother's Education	0.0613	0.0575	0.1837	0.2263	0.0590	0.0522
Single Mother	0.0093	0.0103	0.0891	0.0449	0.0110	0.0068
Family Income	0.0743	0.0679	0.2638	0.3278	0.0617	0.0519
Cognitive Ability	0.1224	0.0950	0.4463	0.3757	0.1047	0.0682
Unobserved Het	0.4855	0.5152	0.1479	0.2172	0.7171	0.7984
All of the above	0.6592	0.6551	0.8069	0.8578	0.8618	0.9059

Chapter 2

Effect of Participation in After-School Activities and Working While in School on High School Performance in the US

2.1 Introduction

Large proportions of students in many developed countries work, both in high school and college. For instance, data from the National Education Longitudinal Study of 1988 (NELS:88) show that in 1990, 56 percent of 10th-grade students in the US were working during school days while this number for, the same cohort, had increased to 70 percent in 1992 when most students were in 12th grade. Almost 20 years later, data from the High School Longitudinal Study of 2009 (HSLS:09) show that 50 percent of 9th-grade students in the US were working during school weeks while this number for the same cohort had decreased to 46 percent in 2012 when they were mostly in 12th grade. This drop in the number of working students could be a result of the 2008-09 economic recession.

One important reason for student employment is the income it brings which may satisfy the students' consumption needs (Baert, Rotsaert, Verhaest, & Omey, 2016). However, research in different disciplines, such as sociology, psychology and economics, shows that the effects of working while in school could be long-lasting and may be a source of problems such as psychological stress (Steinberg & Dornbusch, 1991). There exists a large body of literature in labour economics which will be reviewed in the next section of this paper, that has extensively examined the impact of school-year employment on academic performance and future labour market outcomes (See for example Eckstein & Wolpin, 1999; Hansen, 2008; Oettinger, 1999; Stinebrickner & Stinebrickner, 2003).

An aspect of student employment that has been studied widely is its impact on educational performance (Baert & Vujić, 2018; Buscha, Maurel, Page, & Speckesser, 2012; Hansen, 2008; Stinebrickner & Stinebrickner, 2003). The focus on this matter is not surprising since working while enrolled in school can potentially crowd out time for studying and impair academic performance. If employment during school turns out to be detrimental to academic achievement, it can indirectly affect all later life outcomes that are (to some extent) determined by these achievements, such as wealth and success in the labour market (Chiswick, Lee, & Miller, 2003; Hartog & Oosterbeek, 1998).

For these reasons, the effect of working while in school on academic performance and achievement is important for policymakers. For example, if it turns out that employment while in high school indeed impedes good academic performance, then more restrictions should be put in place on the number of hours teenagers can work while in school. On the other hand, if employment while in school turns out to have a positive effect on academic performance, then it should be encouraged, and special programs should be put in place that facilitate finding part-time jobs for students.

The theory behind the effect of student employment on the educational performance of youth primarily focuses on whether working while in school is a complement to education or a substitute. According to standard human capital theory (Becker, 1975), student employment can be a complement to education because students can learn new general and transferable skills such as work ethics, discipline, and responsibility (Buscha et al., 2012). Since these skills are considered in employers' hiring decisions (Ashworth, Hotz, Maurel, &

Ransom, 2021; Baert & Vujić, 2018), working while in school may aid students in acquiring necessary human capital for a successful transition to the workforce (Geel & Backes-Gellner, 2012; Hotz, Xu, Tienda, & Ahituv, 2002). Working while in school can also change students' intertemporal preferences by making them value their future outcomes and motivate them to work harder in school to reach those outcomes (Oettinger, 1999).

On the other hand, based on the theory of time allocation (Becker, 1965), student employment and education can be substitutes since students have fixed time endowments which employment limits. Hence, if part of the fixed time endowments is used for work, that bygone time cannot be used for improving academic performance anymore (Darolia, 2014) and reduction in time spent on studying, may harm educational outcomes. However, previous studies show that working an extra hour does not necessarily translate into spending one hour less on studying, since student workers may reduce their leisure time instead of cutting back the dedicated time to their studies (Kalenkoski & Pabilonia, 2009, 2012).

Since economic theory does not give us a unique consensus as to the effect of student work on educational performance, researchers usually rely on empirical studies to determine this effect. However, there is a substantial endogeneity problem that researchers face when they are empirically studying the effect of working while in school on educational performance. Endogeneity exists since students who decide to work while in school may differ from students who do not work. These differences between the employed and non-employed students may also affect their academic outcomes.

To be able to infer any causal effect of employment on educational performance, researchers need to control for these common determinants. If not, variation in educational performances due to these pre-existing differences between working and non-working students will be taken as the effect of the difference in work status (Baert & Vujić, 2018; Stinebrickner & Stinebrickner, 2003). These pre-existing differences can be either observable (for example, gender, ethnicity, and parental education) or unobservable to the researcher (for example, motivation and ability). While it is easy to account for observable differences by including them as control variables in the estimation process, it is usually very difficult to do this for the pre-existing unobserved differences.

Researchers have used several different methods to control for the endogeneity problem described above. As reviewed by Neyt, Omey, Verhaest, and Baert (2019), the first generation of studies treated working while in school as exogenous and conducted simple regressions (controlling for a set of observable characteristics). The regression methods used in this first generation of work were ordinary least squares (OLS), linear probability model (LPM) and logit regressions. However, the pre-existing unobservable differences between working and non-working students are generally not controlled for in these regressions and this can lead to biased empirical results.

A second method is matching, specifically, propensity score matching (PSM), the object of which is to compare each working student with a similar student that does not work. This is done through a three-step procedure. The first step is to predict the probability of working as a student (the propensity score) for each individual based on some observed covariates. It is common to use gender, ethnicity, parental education, family income and previous academic performance as covariates for estimating the propensity scores. The next step is to match working and non-working students based on their propensity scores. The last step is to compare the educational performance of these matched students to each other. The matching method assumes that the selection of students into working and non-working groups is random conditional on the covariates used to calculate the propensity score, but this assumption may not be satisfied in practice due to unobserved differences between the two groups.

Another method that is used in many studies is to control for individual fixed effects (Darolia, 2014; Hansen, 2008; Wenz & Yu, 2010). In the fixed effects regression model, time-invariant unobserved heterogeneity between working and non-working students can be controlled for. However, this approach only works if unobserved heterogeneity between working and non-working students is constant over time, an assumption that is not universally accepted.

Other methods using longitudinal data to control for unobserved heterogeneity include the Cox proportional hazard model and difference-in-differences (DiD) models. However, like the fixed effects models, these models make assumptions about the evolution of the unobserved heterogeneity between workers and non-workers over time.

Another method to control for endogeneity of the decision to work is instrumental variable (IV) estimation. This is a common method and the instruments that have been used include local labour market conditions (See for example Beffy, Fougère, & Maurel, 2010; Dustmann & Van Soest, 2008) and variation in labour laws in different states (Lee & Orazem, 2010). However, it is not clear that these instruments are valid (Buscha et al., 2012; Oettinger, 1999; Stinebrickner & Stinebrickner, 2003). For example, Baert et al. (2016) argue that local labour market conditions during high school or college may affect individuals' decision whether to drop out.

Another approach is dynamic discrete choice modelling (See for example Baert & Vujić, 2018; Eckstein & Wolpin, 1999; Montmarquette, Viennot-Briot, & Dagenais, 2007). In these models, school and work decisions as well as outcomes are modelled jointly (as discrete choices) but the outcomes are allowed to differ for a finite number of unobserved heterogeneity types in the data. An essential assumption in these models is the orthogonality of the unobserved and observed determinants of the modelled outcome which is also a strong assumption.

In this paper, I use data from two American surveys (NELS:88 and HSLS:09) to study the effect of participation in different activities during the school year and the intensity of the participation, on academic performance. Similar to Hansen (2008), and unlike most of the previous literature which has focused mainly on student employment, this paper also considers extracurricular activities. Studying the impact of participation in extracurricular activities on educational attainment can be useful in the sense that, if the effect of participation in these activities turns out to be positive, we may conclude that there is no crowding out effect from participating in after-school activities (including working) on educational performance.

Participation in extracurricular activities is common. Data from NELS88 show that in 1990, 72 percent of students (mostly in 10th grade) participated in some form of extracurricular activity. This number for 1992, when most students were in 12th grade, was 75 percent. The corresponding proportions for the 2009 cohort, were 82 percent for 9th graders and 81 percent for students in 12th grade. Since it is likely that participating in extracurricular activities and working while in school are chosen endogenously, different methods have been used in this paper to study the impact of participation on academic outcomes. For working while in school, the estimations show that in 1990, working while in 10th grade did not have any statistically significant impact on academic performance, but in 1992, when most of the cohort was in 12th grade, it decreased the GPA by 0.06 points. Almost 20 years later, in 2009, participation in the workforce in 9th grade decreased the GPA by 0.025 points and working in 2012 decreased the GPA by 0.07 points. Participation in extracurricular activities in all of the above years has a positive significant effect on academic performance. Participation in extracurricular activities in 1990, increased the GPA by 0.198 points and this effect increased to 0.233 points in 1992. The positive effect of participation in extracurricular activities on GPA for the younger cohort in 2009 and 2012 were respectively 0.142 and 0.104 points.

The remainder of the paper is organized as follows. The next section reviews the related literature. Section 3 describes the data; section 4 discusses the methodology and section 5 presents the results. Section 6 contains the conclusion and some suggestions for future research.

2.2 Literature Review

Over the past few decades, an extensive body of work has examined the effect of working while in school on educational achievements. A selection of these studies is briefly reviewed in this section from the oldest to the most recent.

Oettinger (1999) studies how student employment affected high school students surveyed between 1979 and 1983. He finds that employment at modest weekly hours results in higher grades within each grade level, but summer transitions, in and out of employment, were causing small performance declines and gains, respectively. While his findings show that the effect of participation in school-year employment was quite small, large hours of working during school had a large, statistically significant negative impact on the academic performance of racial minorities. Summer employment did not affect grades, suggesting a "crowding out" effect from student employment on study time.

Eckstein and Wolpin (1999) estimate a structural model of high school attendance and work decisions. Their estimates show that students who drop out of high school have different characteristics than those who graduate – they have lower school ability and/or motivation, they have lower value for graduation, they have a comparative advantage at jobs that do not need a high school degree, they value leisure more than school attendance. They also found that working while in school reduces academic achievements. However, policy experiments based on the model's estimates show that even the most restrictive laws that prohibit students from working while in high school would have only a small effect on the rate of graduation from high school among white males.

Stinebrickner and Stinebrickner (2003) use data from a college with a mandatory work-study program to study the relationship between student employment and academic performance. They take the job that a student is assigned in the first semester as an instrument for hours worked. They also run OLS and fixed effect regressions and find that working while in school has a positive effect on academic performance whereas their results from the IV estimation show that working additional hours harms academic performance. They conclude that results from OLS and FE regressions are biased and overstating the effect so much that they have become positive.

Montmarquette et al. (2007) study the determinants of student employment, academic achievement, and the decision to drop out of high school. They use Canadian data on high school students and dropouts and define utility functions for working and studying to model the choices of students who they assume consist of two types (those who prefer studying and those who prefer to work) and jointly estimate the model using maximum likelihood estimation method. They show that being a female, attending a private school, and living with educated parents are strongly related to having a preference for schooling over working while in school. They also find that working fewer hours per week while in school does not necessarily harm one's success in school. Their results show that the decision to drop out is impacted by the law on the minimum age for adolescent labour, high minimum wages, and low unemployment rates.

Dustmann and Van Soest (2008) analyze students' part-time employment, their academic performance, and their dropout decisions. They use data from the UK National Child Development Study. They incorporate working part-time, school performance and dropout decisions in a three-equation model that is estimated simultaneously. To identify the effects of hours worked and exam success in the school leaving equation, they exclude the occupational and educational status of the parents and replace them with variables which reflect the wish of the parents that the child proceed into higher education.This implies that parents' education and occupational status have no direct effects on the decision to continue in school, beyond those captured by the parents' expressed interest in the child's educational career. They find working part-time during school to have only small negative effects on female students' exam outcomes, and to have no effect on males. Also, part-time work has a small negative and only marginally significant effect on the decision to stay at school for males, but not for females.

Hansen (2008) uses data from the Youth in Transition Survey (YITS) from Statistics Canada to study the effect of participation in different activities including work and extracurricular activities on academic performance. The difference between his study and previous literature is the consideration of non-work activities in his study whereas the previous literature only focuses on working while in school. To deal with the probable endogeneity issue, he uses several different methods including fixed effects regression to examine the impact of participation on academic outcomes. His results show that working while in school harms academic performance in grade 10 and this negative impact seems to be persistent over time and affects academic performance in grade 11 significantly. However, working while in grade 11 does not have a significant effect on GPAs in grade 11. Also, he finds no evidence that working a few numbers of hours during the school year is beneficial in either grade. He also finds out that participation in school activities has significant and positive effects on academic performance.

Sabia (2009) examines the relationship between student employment and academic outcomes of students under age 16 using data from the National Longitudinal Study of Adolescent Health. OLS estimates show a significant positive relationship between a few hours of school-year work and GPA. However, fixed effects estimates show a substantially diminished effect for school-year employment on GPA which shows that much of the positive effect can be explained by individual unobserved heterogeneity.

Beffy et al. (2010) study the effect of part-time work on educational attainment. They used samples from the French Labor Force Surveys between 1992 and 2002. They estimate Probit models with two simultaneous regression equations for working while studying and for success on the final exam, plus the decision to continue the following year in one of the models. They use differences in low-skilled youth unemployment rates and their interactions with the father's socioeconomic status as instrumental variables to identify the effect of part-time work on educational attainment. Their results show that a part-time job has a large and statistically significant negative effect on the graduation probability.

Wenz and Yu (2010) study the effect of student employment on academic achievement using OLS, Tobit and Fixed Effects regressions. The results show that employment has small negative effects on student grades which increase with each extra work hour. They use a custom dataset based on students at a traditional regional state university that has information on student motivations. They find that students who work because of financial constraints have lower grades on average than students who work for career-specific skills but higher grades than those students who have a desire for general work experience.

Buscha et al. (2012) used NELS:88 data to investigate the effect of working during grade 12 on graduation. They used a propensity score matching method combined with difference-in-differences. They controlled for observed and unobserved characteristics associated with part-time work decisions, and once those factors were controlled for, they found that working part-time in grade 12 has little to no effect on reading and math scores. Overall, their results show only a negligible academic cost from part-time work by the end of high school.

Darolia (2014) uses data from the 1997 cohort of National Longitudinal Study of Youth to examine the effect of working, on grades and credit completion for university students in the US. He uses fixed effects and GMM regressions to deal with the probable endogeneity of working and academic outcome that varies over time. The equation is first-differenced to eliminate time-invariant unobserved effects and the lagged endogenous outcome variable is instrumented with earlier lags. An assumption with the system GMM estimator is that the first differences of the instruments are uncorrelated with time-invariant student fixed effects. He finds no evidence that working more hours can harm students' grades, but that full-time students complete fewer credits per term when increasing work.

Behr and Theune (2016) examine the effect of working on time to first degree at German universities. They use data from the 'Absolventen panel' 2001 and matching. Their results show that off-campus work indeed delays graduation.

Scott-Clayton and Minaya (2016) use a matching method to estimate the effects of the Federal Work-Study Program (FWS) in the US. Their results show that about fifty percent of individuals who participated in the FWS program would have worked even if there was no subsidy. For these individuals, the FWS reduces the number of hours worked, improves academic outcomes and has little effect on early post-college employment. For students who would not have worked in the absence of FWS, the pattern reverses. The FWS has no academic benefit for this group of students and does not show any significant effect on early post-college employment.

Baert et al. (2016) examine the direct and indirect effect (through educational achievement) of student work during high school on later employment outcomes. They jointly model student work and later schooling and employment outcomes as a chain of discrete choices accounting for unobserved heterogeneity. They use longitudinal Belgian data and find that students who work during the summer of secondary education are more likely to have a job three months after finishing school and this is despite the indirect negative effect of working on tertiary education enrolment. This positive impact of student work experience on later labour force outcomes is higher when students also work during the academic year and decreases for later employment outcomes.

2.3 Data

My analysis is based on data from two datasets, NELS88 and HSLS09. NELS88 is a nationally representative sample of 27,394 young American males and females who were in 8th grade (13-16 years old) when they were first surveyed in 1988 while the HSLS09 consists of a nationally representative sample of 23,503 young males and females who were in 9th grade (13-17 years old) in 2009. For both cohorts, there is detailed information on family background and income, individual cognitive skills (measured by their scores in a standardized math test), GPAs and information on participation status in the workforce and extracurricular activities and the intensity of the participation. Interviews were conducted in 1988, 1990, 1992, 1994 and 2000 for the first cohort and in 2009, 2012, 2013, 2016 and 2017 for the second cohort.

To be included in the sample, an individual respondent must have completed the standardized math test. This requirement was imposed since the test scores are needed to try to remove some of the bias of the estimated impact of student employment on high school performance. Also, all individuals with incomplete information on their participation in extracurricular activities and employment were removed. Finally, respondents with missing information on their grade point average or any of the included family background variables were dropped. These reductions reduced the sample to 4,901 respondents for the 1988 cohort and 8,917 respondents for the 2009 cohort. Some of the most important characteristics of my samples are found in Table 2.1 (devoted to summary statistics).

It can be observed from this table that in the span of about 20 years, the average number of siblings has decreased significantly. That could indicate that the opportunity cost of having more kids increased between the late 1980s and late 2000s. Another observation is that Grade Point Averages (GPAs) had increased for 2009 compared to the 1988 cohort. The average GPA in grade 12 in 1992 was 2.43 while this number was 2.67 in 2012. This might be due to differences in the quality of education these two cohorts received or due to grade inflation.

Another observable difference between the two cohorts is their average family income.

For both surveys, information on family income from all sources was gathered in the first survey year. Hence, for NELS88 the variable shows family income from all sources in 1987 and for HSLS09, in 2008. I calculated the real family income in the year 2000 dollars for both cohorts. During 21 years, the average family income in my sample increased from $65,669 to $70,095 which is about 0.3% per year. The last difference between the two cohorts is that the proportion of mothers who had some college education in the 2009 cohort is higher than the proportion of fathers who have some college education, contrary to the 1988 cohort.

Table 2.2 compares the mean values of selected variables from the main samples of NELS88 and HSLS09 and the sub-samples used in this paper, to show that the values in these samples are comparable. It can be observed from the table that the means in the samples used in this paper are close to the ones in the main samples.

My analysis uses information from the first three rounds of NELS88 and the first two rounds of HSLS09 while the students are still attending high school. Specifically, information on the mother's education, family income, urban residency, and gender was taken from the 1988 cycle for NELS88 and the 2009 cycle for HSLS09. For the 1988 cohort, information on high school grade point averages and participation in various activities, including work, were obtained from the 1990 and 1992 cycles. For the younger cohort, this information was attained from the 2009 and 2012 cycles. Student's grade point averages have four categories, 4 for A and 1 for D.

Table 2.3 shows a description of participation in different activities (extracurricular activities and work) for respondents from both cohorts. As can be seen, participation in these types of activities is common. During the 1989-1990 school year, 72% of students participated in some form of extracurricular activity and around 56 percent of students worked. In the 1991-1992 school year, participation in extracurricular activities increased by 5 percentage points and the proportion of students who worked for pay during the school year increased (to around 70 percent). For the 2009 cohort, during the 2008-2009 school year, around 85% of students participated in some form of extracurricular activity and around

Table 2.1: Descriptive Statistics

	1988 Cohort	2009 Cohort
Variable	Mean	Mean
Grade Point Average (1990 or 2009)	2.50	2.73
Proportion with GPA A	8.65%	17.88%
Proportion with GPA B	42.34%	45.91%
Proportion with GPA C	39.13%	27.69%
Proportion with GPA D or below	9.88%	8.52%
Grade Point Average (1992 or 2012)	2.43	2.67
Proportion with GPA A	8.94%	14.25%
Proportion with GPA B	38.00%	47.68%
Proportion with GPA C	40.59%	29.58%
Proportion with GPA D or below	12.47%	8.48%
Number of Siblings	2.10	1.50
Male	0.46	0.48
Rural	0.33	0.24
Family Income	\$65,669	\$70,095
Mother's education		
Below High School	11.32%	5.75%
High School Graduate	35.40%	37.27%
Some Post-secondary Education	53.27%	56.98%
Father's Education		
Below High School	11.75%	6.65%
High School Graduate	30.09%	38.27%
Some Post-secondary Education	58.16%	55.08%
Math Test Score (1990 or 2009)	48.32	43.86
Math Test Score (1992 or 2012)	53.05	72.96
Observations	4,901	8,917

49% of students worked for pay. In the 2011-2012 school year, participation in both activities decreased. One reason for this decrease in participation in activities might be the Great

Table 2.2: Mean Values of Selected Variables

	NELS88	Sample of 1988	HSLS09	Sample of 2009
GPA (1990/2009)	2.37	2.50	2.61	2.73
GPA (1992/2012)	2.26	2.43	2.59	2.67
Math Test Score (1988 or 2009)	37.42	39.92	42.56	43.86
Male	0.48	0.46	0.51	0.48
Rural	0.31	0.33	0.23	0.24
Family Income	$60,998	$66,269	$68,412	$70,095
Mother's educ	Junior College	Junior College	Junior College	Junior College
Observations	12,144	4,901	23,503	8,917

Recession. As we will see later in the paper, family income shows a statistically significant positive effect on participation in extracurricular activities. The recession may have affected the family income, which in turn may have caused a decrease in the participation rate in extracurricular activities. The recession at the same time affected the labor market. Data from the US Bureau of Labour Statistics show that the unemployment rate among those 16-19 years old was 22.05% between September 2008 to August 2009 while this number, two years later, from September 2011 to August 2012, had increased to 24.07%. Higher unemployment rates may have discouraged students from participating in the labour market and made it more difficult for them to find a job.

The lower panels of Table 2.3 provide some information on how much time students spent on each activity. Unfortunately, there is no information on the number of hours spent on extracurricular activities in 2012. Among students who work, a noticeable proportion work more than 10 hours. The proportion of students who participate for more than 10 hours per week in extracurricular activity is also large.

To discover who participated in different types of activities, participation in each activity was regressed on selected observable characteristics. The results are in Tables 2.4.

For example, during the 1989-1990 school year, participation in extracurricular activities was significantly and positively correlated with mother's education and family income. This may indicate that students from less well-off backgrounds are unable to participate in these

Table 2.3: Participation in different activities during school years 1990, 1992, 2009, 2012

	Type of Activity	
	Extracurricular	Paid Work
1988 Cohort		
Proportion Participating		
Grade 10 (1990)	0.72	0.56
Grade 12 (1992)	0.77	0.70
2009 Cohort		
Proportion Participating		
Grade 9 (2009)	0.85	0.49
Grade 12 (2012)	0.84	0.46

	Extracurricular	Paid Work
Proportion Spending		
Between 1 to 9 hours per week		
Grade 10 (1990)	54.72%	37.36%
Grade 12 (1992)	49.15%	18.47%
Grade 9 (2009)	39.33%	39.14%
Grade 12 (2012)	-	16.88%
10 hours or more per week		
Grade 10 (1990)	17.73%	18.67%
Grade 12 (1992)	27.63%	49.91%
Grade 9 (2009)	43.96%	10.03%
Grade 12 (2012)	-	28.84%

activities because of monetary constraints. Although it could also be due to differences in preferences. Work in the 1989-1990 school year however does not show any significant correlation with the mother's education or family income.

For the 1991-1992 school year, there is still a significant and positive correlation between family income, maternal education, and participation in extracurricular activities. As for working in 1992 when most of the students were in grade 12, Table 2.4 shows a statistically significant negative effect from family income and mother's education on working.

During the 2008-2009 school year, participation in extracurricular activities still showed the same positive correlation with the mother's education and family income. Participation

Table 2.4: Determinants of Participation in Different Activities

	Type of Activities							
	Extracurricular				Paid Work			
	1990	1992	2009	2012	1990	1992	2009	2012
Male	-0.080**	-0.044**	-0.010	-0.015*	0.112**	-0.025*	-0.013	-0.011
	(-6.33)	(-3.65)	(-1.31)	(-1.89)	(7.92)	(-1.92)	(-1.23)	(-1.05)
Rural	0.067**	0.049**	0.022**	0.010	0.036**	-0.023*	0.003	0.001
	(4.98)	(3.83)	(2.45)	(1.06)	(2.39)	(-1.65)	(0.26)	(0.10)
Mother's Education	0.036**	0.025**	0.039**	0.026**	0.002	-0.014**	-0.016**	-0.011**
	(8.96)	(6.40)	(13.37)	(8.62)	(0.49)	(-3.20)	(-3.64)	(-2.40)
Family Income	0.001**	0.0005**	0.001**	0.001**	-0.0002	-0.001**	-0.00001	0.0002
	(4.55)	(3.72)	(10.97)	(8.78)	(-1.32)	(-4.25)	(-0.01)	(1.22)

in work, however, has a significant and negative correlation with the mother's education but no significant correlation with family income. And, in the 2011-2012 school year, parental income is uncorrelated with the decision to work but is still correlated with participation in extracurricular activities.

2.4 Methodology

I start my study with a basic empirical model to estimate the effect of working and participation in extracurricular activities on academic performance, measured by high school GPA. The independent variables include dummies for whether or not the individual participated in work or extracurricular activities and information on gender, mother's level of education, family income and whether the school is located in a rural area.

$$GPA_i = \beta_0 + \beta_1 d_{extra,i} + \beta_2 d_{work,i} + \beta_3 male_i + \beta_4 Rural_i + \beta_5 Medu_i + \beta_6 Faminc_i.$$

However as discussed above, the OLS estimates of the effects of participation in different activities on academic performance may be biased. For example, if those who participate in activities are also more motivated in their schoolwork, OLS estimates will be biased and include the effect of motivation as well. One way to address this problem is to include proxy variables for the unobserved characteristics that are believed to be correlated with activities. For example, the standardized math test scores that are reported in NELS88 and HSLS09 may be used for this purpose as a measure of ability.

$$GPA_i = \beta_0 + \beta_1 d_{extra,i} + \beta_2 d_{work,i} + \beta_3 Math_i + \beta_4 male_i + \beta_5 Rural_i + \beta_6 Medu_i + \beta_7 Faminc_i.$$

Since I have access to panel data, an alternative to using proxy variables is to take the difference of the regression equations over time. This difference will remove any time-invariant unobserved characteristics of the respondents that we expect to be the cause of endogeneity. In this paper, I look at differences in GPAs between rounds 2 and 3 for NELS88 and rounds 1 and 2 for HSLS09 and regress each difference on the corresponding differences in participation in work or extracurricular activities. OLS estimates of these regression specifications will be consistent as long as the changes in the unobserved component of GPAs between two grades are uncorrelated with the changes in participation in activities between those two grades.

$$\Delta GPA_i = \beta_0 + \beta_1 \Delta d_{extra,i} + \beta_2 \Delta d_{work,i} + \beta_3 \Delta Math_i.$$

However, there may be components of the error terms that are due to unobserved characteristics and correlated with participation in activities. In this case, the fixed effects estimates will not measure an unbiased estimate of the effect of participation if these unobserved characteristics change over time. If that is the case, the solution may be the implementation of an instrumental variables (IV) estimator. To identify the parameters, we need exclusion restrictions. Generally, it is very difficult to find valid instruments that satisfy the exclusion restrictions, and the results may be sensitive to the choice of such restrictions. Given these concerns and the fact that I do not have access to data that can be used as a valid instrument, I do not report any IV estimates in this paper.

Up to this part, I have focused on participation in activities, but the intensity of such activities may also be important. To examine this, I consider regression equations where the indicator variables are replaced by intensity variables. It should be noted that the endogeneity problems remain, and they are addressed using similar methodologies.

2.5 Results

The first column of Table 2.5 presents least squares estimates using information on activities from the 1989-1990 school year. These estimates suggest that participation in extracurricular activities significantly improves a student's GPA, but employment appears to not have a statistically significant effect on academic performance. In column 2, the same regression was estimated based on activities and outcomes in the 1991-1992 school year. The patterns are the same except for the effect of working, which is now negative and statistically significant. The third and fourth columns show the results for the 2009 cohort. In grade 9 and in 2012 when most students were in grade 12, working harms GPA but extracurricular activities had the same positive effect as for the previous cohort. From these results, we may conclude that working while in high school is detrimental to academic performance and participation in extracurricular activities has a positive effect on GPA. However, as discussed earlier in the paper, it is likely that these estimates simply reflect systematic unobserved differences among students who choose to participate or not participate in after-school activities. For example, more talented and motivated students might be more likely to participate in extracurricular activities and the estimates in Table 2.5 are unable to control for this possibility.

One way to reduce the potential bias in the OLS estimates is to include proxy variables for unobserved individual characteristics. Table 2.6 contains results when the standardized math scores were added to the set of regressors. From column 1 we see that participation in extracurricular activities is still beneficial and has a positive statistically significant effect on students' GPA. As expected, the estimates are somewhat smaller than the ones in Table

Table 2.5: The Effect of Participation in Activities on High School Grade Point Average (GPA)

	School year			
	1989-1990	1991-1992	2008-2009	2011-2012
Activities				
Extracurricular	0.307**	0.361**	0.196**	0.131**
activities	(12.54)	(14.33)	(7.96)	(5.66)
Paid Work	0.015	-0.052**	-0.090**	-0.093**
	(0.70)	(-2.12)	(-5.32)	(-5.62)
Male	-0.090**	-0.216**	-0.286**	-0.291**
	(-4.14)	(-9.79)	(-16.95)	(-17.74)
Rural	-0.007	0.035	0.038*	-0.001
	(-0.28)	(1.46)	(1.87)	(-0.04)
Mother's Educ	0.083**	0.105**	0.120**	0.108**
	(11.75)	(14.49)	(16.63)	(15.04)
Family Income	0.001**	0.002**	0.002**	0.002**
	(5.48)	(7.84)	(12.79)	(11.99)
Mean GPA	2.50	2.43	2.73	2.68
R^2	0.09	0.14	0.13	0.11

2.5. This suggests that there indeed is a positive correlation between participation in after-school activities and scholastic ability and that when such ability measures are omitted, the participation variables pick up some of this effect as well.

While the effects of participating in non-work activities were reduced slightly but stayed positive, the effect of working on GPA changed sign but remained statistically insignificant in the 1989-1990 school year. Clearly, the inclusion of test scores has an impact on the estimates. The estimates for math scores have the expected signs (positive correlation between scores and GPA). Thus, the results again provide strong indications that extracurricular activities are positively associated with GPA. This finding is robust, and the effect is larger in grade 12 compared to grade 10.

The same process was repeated for school years 2008-2009 and 2011-2012 and the results can be found in columns 3 and 4 of Table 2.6.

The third column of Table 2.6 shows that, in the 2008-2009 school year, participation in extracurricular activities still significantly improves a student's GPA. Employment on the

Table 2.6: The Effect of Participation in Activities on High School Grade Point Average (GPA), with controls for math test scores

	School year			
	1989-1990	1991-1992	2008-2009	2011-2012
Activities				
Extracurricular	0.183**	0.214**	0.116**	0.075**
activities	(7.90)	(9.44)	(5.31)	(3.51)
Paid Work	-0.021	-0.056**	-0.026*	-0.061**
	(-1.07)	(-2.72)	(-1.73)	(-4.07)
Math Test Score	0.029**	0.036**	0.036**	0.030**
	(31.98)	(41.51)	(54.26)	(42.49)
Male	-0.113**	-0.244**	-0.315**	-0.315**
	(-5.68)	(-12.89)	(-21.27)	(-20.99)
Rural	0.030	0.077**	0.066**	0.021
	(3.71)	(3.69)	(3.70)	(1.16)
Mother's Educ	0.045**	0.046**	0.056**	0.055**
	(5.55)	(6.96)	(8.96)	(8.38)
Family Income	0.0001	0.0003*	0.001**	0.001**
	(0.43)	(1.71)	(6.66)	(6.61)
Mean GPA	2.50	2.43	2.73	2.68
R^2	0.25	0.37	0.33	0.26

other hand appears to harm academic performance. In column 4, the same regression was estimated based on activities and outcomes in the 2011-2012 school year. The patterns are the same as the 2008-2009 school year. From these results, we may conclude that working during the school year has a detrimental effect on academic performance in high school. The results also show that participation in extracurricular activities does have positive effects on the GPA. The estimates for math scores have the expected signs (positive correlation between scores and GPA).

While the entries in Tables 2.5 and 2.6 show that participation has a statistically significant effect on academic achievement, it is difficult to assess the magnitude of these effects from the OLS regression results, since the dependent variable is categorical rather than continuous. Hence, OLS may not be the best-suited estimation method. To evaluate whether the results are sensitive to the choice of methodology, the regression specifications described in Table 6 were re-estimated using ordered logit models instead. Using estimates from such a model, it is possible to calculate the effect of a change in an independent variable on the predicted probability that a certain GPA is obtained. The results are reported in Table 2.7.

In the first four columns, the effects of participation in extracurricular activities are shown. They suggest that such participation reduces the probability of having a GPA below B. Results from the four last columns are consistent with results from Table 2.6 and show that working in earlier years of high school for the 1988 cohort does not have any significant effect on educational performance. However, working in the later years of high school, specifically in 12th grade, has a significant negative effect on the students' GPAs. The magnitudes of these effects are rather high. For example, participating in extracurricular activities while in 10th grade in 1990 increases the probability of having a GPA of A, by 43%. In 1992, when most students were in 12th grade, this was 49%. These numbers are quite large. On the other hand, working while in school in 2012 decreases the probability of having a GPA of A by 13% and increases the probability of having a GPA of D or less than D by 14%.

An alternative way to deal with the potential endogeneity of participation in activities is to assume that the unobserved effects – which are possibly correlated with activities – do not change over time. If this assumption holds, we may be able to obtain valid estimates by taking first differences to remove these time-invariant and unobserved individual characteristics. The results are shown in Table 8 for both cohorts. The dependent variable is defined as the difference in GPA between the school years 1989-1990 and 1991-1992 for the 1988 cohort and between the school years 2008-2009 and 2011-2012 for the 2009 cohort. This difference is regressed on changes in participation in different activities. Hence, the effects are identified from those who change their participation status between the two years. The estimates show that participation in extracurricular activities had no significant effects on GPA both in the early 1990s and in the early 2010s. This is different than the results from OLS and ordered logit estimations. This could be due to a lack of variation in the data because of the limited number of individuals in the sample who changed their participation in

Table 2.7: The Effect of Participation in Activities on High School Grade Point Averages (GPA) in 1990 and 1992, with Controls for Math Test Scores; Marginal Effects from Ordered Logit Model

	Type of Activity							
	Extracurricular				Work for Pay			
	1990	1992	2009	2012	1990	1992	2009	2012
Effect on the probability of having a GPA of D or below	-0.042**	-0.057**	-0.021**	-0.013**	0.006	0.015**	0.005*	0.012**
Effect on the probability of having a GPA of C	-0.058**	-0.051**	-0.033**	-0.022**	0.009	0.013**	0.009*	0.020**
Effect on the probability of having a GPA of B	0.063**	0.065**	0.017**	0.015**	-0.009	-0.017**	-0.004*	-0.014**
Effect on the probability of having a GPA of A	0.037**	0.044**	0.037**	0.020**	-0.005	-0.011**	-0.010*	-0.018**

Predicted proportions in range of GPA D/less are 0.0988(1990), 0.1247(1992), 0.0852(2009), 0.0848(2012)
Predicted proportions in range of GPA C are 0.3913(1990), 0.4059(1992), 0.2769(2009), 0.2958(2012)
Predicted proportions in range of GPA B are 0.4234(1990), 0.3800(1992), 0.4591(2009), 0.4768(2012)
Predicted proportions in range of GPA A are 0.0865(1990), 0.0894(1992), 0.1788(2009), 0.1425(2012)

extracurricular activities status between the two periods. The effect of working is negative but statistically insignificant for the 1988 cohort but this effect is negative and significant for the 2009 cohort.

Much of previous research on the effects of working on academic achievement has found that working a few hours per week may be beneficial to academic performance while working many hours (generally more than 15 hours) negatively affects academic outcomes. In Table 2.9 this issue is examined using a regression specification that includes math test scores.

Table 2.8: Fixed Effects Estimates from Regressions of High School Grade Point Averages (GPA) on Participation in Activities

	Dependent Variable Difference in GPA	
	1988 Cohort	2009 Cohort
Extracurricular Activities	-0.028	-0.009
	(-1.55)	(-0.55)
Work for Pay	-0.013	-0.088**
	(-0.90)	(-2.21)
Intercept	2.495**	2.754**
	(155.47)	(114.80)

In the first column, the dependent variable of the regression is GPA in 1989-1990, while in the second column, the dependent variable is GPA in 1991-1992. In 1989-1990 there is a strong correlation between participation in extracurricular activities and GPA. The positive effect increases, the more hours that are spent on these activities. The lower panel shows that working in the 1989-1990 school year, when most of the students were in 10th grade, does not have any significant negative effect on the students' GPAs. Working a moderate number of hours (between 1 to 9 hours per week) in the 1991-1992 school year did not have a significant impact on educational performance but working more than 10 hours per week shows a significant negative effect on students' GPAs.

The last two columns present the results of similar regressions for the 2008-2009 and 2011-2012 school years. There is no information in HSLS09 on the number of hours students were involved in extracurricular activities in 2011-2012, hence the fourth regression was only estimated for work hours. The results for grade 9 students show that the number of hours spent on extracurricular activities has a positive correlation with academic outcomes and the more hours spent on these activities, the larger the effect. As for hours spent working in the 2008-09 school year, a moderate number of hours do not show any significant effect on students' GPAs but working for more than 10 hours per week shows a negative significant impact on academic performance. The results for the 2011-12 school year show that working less than 10 hours per week has a positive effect on the individual's GPA while working

Table 2.9: Intensity of Activities and High School GPA, with Controls for Math Test Scores

	Dependent Variable: GPA			
	1990	1992	2009	2012
Extracurricular Activities				
1 to 9 hours	0.170**	0.183**	0.068**	-
	(7.08)	(7.55)	(2.95)	
10+ hours	0.228**	0.256**	0.157**	-
	(7.34)	(9.54)	(6.92)	
Paid Work				
1 to 9 hours	-0.027	0.013	-0.016	0.046**
	(-1.24)	(0.47)	(-1.01)	(2.23)
10+ hours	-0.011	-0.075**	-0.095**	-0.119**
	(-0.42)	(-3.42)	(-3.57)	(-6.78)

more than 10 hours per week has a significant negative impact on GPA.

These results are in line with results presented in Hansen (2008) which implies that the negative effect of working while in school arises not because students spend many hours working and it crowds out their study time; instead, the negative effect appears to be due to the type of activity the students engage in. It seems as if the jobs that students hold do not provide any skills they can use to their benefit in school.

To further illustrate the impact of hours of work on high school performance, Table 2.10 shows the marginal effects from ordered logit models. The results show that working does not have any beneficial or detrimental impacts on GPA in 1990. The results in the second and the sixth columns, however, show that while working up to 10 hours per week does not have a significant impact on GPA, working more than 10 hours per week significantly decreases the probability of earning a grade higher than B in 1992. For example, working more than 10 hours per week decreases the probability of earning an A by 21%.

Columns 3 and 7 show the results of the same regression for 2009. The results show that working less than 10 hours per week does not have any statistically significant effect on the probability of having a GPA higher than B but working more than that, decreases this probability. For example, working more than 10 hours will decrease the probability of

Table 2.10: Intensity of Working and High School GPA, with Controls for Math Test Scores in 1989-1990. Marginal Effects from an Ordered Logit Model

	Average Hours of Work Per Week							
	1 to 9 hrs				10+ hrs			
	1990	1992	2009	2012	1990	1992	2009	2012
Effect on the probability of having a GPA of D or below	0.006	-0.006	0.002	-0.009**	0.002	0.025**	0.016**	0.023**
Effect on the probability of having a GPA of C	0.009	-0.006	0.003	-0.015**	0.003	0.022**	0.025**	0.039**
Effect on the probability of having a GPA of B	-0.010	0.007	-0.001	0.010**	-0.004	-0.029**	-0.013**	-0.027**
Effect on the probability of having a GPA of A	-0.006	0.005	-0.003	0.013**	-0.002	-0.019**	-0.029**	-0.035**

Predicted proportions in range of GPA D or below are 0.0988(1990), 0.1247(1992), 0.0852(2009), 0.0848(2012)
Predicted proportions in range of GPA C are 0.3913(1990), 0.4059(1992), 0.2769(2009), 0.2958(2012)
Predicted proportions in range of GPA B are 0.4234(1990), 0.3800(1992), 0.4591(2009), 0.4768(2012)
Predicted proportions in range of GPA A are 0.0865(1990), 0.0894(1992), 0.1788(2009), 0.1425(2012)

having a grade point average of A by 16.2 percent.

Results in columns 4 and 8 show that working less than 10 hours per week improves the probability of earning better GPAs but working more than 10 hours decreases this probability. For example, working between 1 to 9 hours per week will decrease the probability of earning a GPA of D or less than D by 10.6% and working more than 10 hours per week increases this probability by 27%.

Next, I divided the extracurricular activities into two subgroups: Sports (physical activity) and hobbies (participation in different clubs, music groups, artistic activities, etc).

The logic here is that these subgroups of activities might have different impacts on the educational outcomes of individuals. For example, participation in science and math clubs may complement schoolwork and improve students' GPAs. The results from repeating Table 2.9's regressions, this time with separate variables for sports and hobbies, are presented in Table 2.11.

These results show that participation in both types of extracurricular activities has a positive effect on GPA in each year, except for 2012, when the effect of participation in hobbies on GPA is insignificant.

Table 2.11: The Effect of Participation in Sports and Hobbies on High School Grade Point Average (GPA), with controls for math test scores

	Dependent Variable: GPA School Year			
	1989-1990	1991-1992	2008-2009	2011-2012
Activities				
Sports	0.108**	0.050**	0.047**	0.056**
	(4.87)	(2.45)	(2.96)	(3.59)
Hobbies	0.220**	0.186**	0.118**	0.025
	(9.51)	(7.05)	(6.33)	(1.53)
Paid Work	-0.032	-0.059**	-0.028*	-0.062**
	(-1.61)	(-2.83)	(-1.88)	(-4.13)
Math Test Score	0.029**	0.037**	0.036**	0.030**
	(32.11)	(41.96)	(53.97)	(42.48)
Male	-0.105**	-0.254**	-0.312**	-0.319**
	(-5.21)	(-12.63)	(-20.90)	(-20.76)
Rural	0.021	0.080**	0.064**	0.022
	(0.97)	(3.84)	(3.63)	(1.21)
Mother's Educ	0.032**	0.043**	0.053**	0.055**
	(4.85)	(6.66)	(8.41)	(8.32)
Family Income	-0.00001	0.0003	0.001**	0.001**
	(-0.06)	(1.40)	(6.20)	(6.44)
Mean GPA	2.50	2.43	2.73	2.68
R^2	0.26	0.36	0.33	0.26

Up to this point in the paper, to avoid dealing with the issue of high school dropouts which complicates the study, the regressions were estimated for individuals who graduated high school. That is, individuals who dropped out of high school at any time during the period of study were excluded from the sample, since the GPA of these individuals is missing in certain years. However, it is indeed important to study the effects of participation and intensity of participation in these groups of activities for dropouts as well. To do so, I defined a variable which is set equal to 1 if the individual drops out in each of the school years 1991-1992 and 2011-2012 and 0 otherwise. For example, the variable "dropout1992" is set equal to 1 if the person drops out by the end of 1992 and is set equal to 0 otherwise. I then estimated logit regressions for the dropout variable on participation in activities and background characteristics. The results are presented in Table 2.12.

The results show that in 1991-1992, participation in extracurricular activities decreased the probability of dropping out of high school by 4.2%. Working while in high school doesn't seem to have any significant effect on the probability of dropping out in this year.

Table 2.12: The effect of participation in extracurricular activities and paid work on the probability of dropping out of high school

	Dependent Variable: Whether drop out or not (ME from logit)	
	1991-1992	2011-2012
Activities		
Extracurricular	-0.042**	-0.064**
activities	(-7.20)	(-7.85)
Paid Work	0.006	0.019**
	(1.08)	(2.66)
Math Test Score	-0.002**	-0.004**
	(-5.58)	(-12.63)
Male	0.006	0.026**
	(1.18)	(3.67)
Rural	0.005	0.001
	(0.10)	(0.17)
Mother's Educ	-0.003*	-0.023**
	(-1.72)	(-6.53)
Family Income	-0.0001	-0.001**
	(-1.04)	(-6.78)

In the 2011-2012 school year, the results show that participation in extracurricular activities decreases the probability of dropping out by 6.4% and. Working in this cohort has a significant impact on the probability of dropping out of high school. It increases this probability by 1.9%.

The last set of results are the effects of the intensity of participation in extracurricular activities and working on the probability of dropping out for both cohorts. There is no information on the intensity of extracurricular activities in the 2009 cohort, thus the study was done only for work intensity for that cohort. The results are presented in table 2.13.

Table 2.13: The effect of intensity of participation in extracurricular activities and paid work on the probability of dropping out of high school

Dependent Variable: Whether drop out or not (ME from logit)		
	1991-1992	2011-2012
Extracurricular		
1-9 hours	-0.040**	-
	(-6.29)	
10+ hours	-0.045**	-
	(-5.42)	
Work		
1-9 hours	-0.013	-0.015
	(-1.43)	(-1.38)
10+ hours	0.001	0.027**
	(0.25)	(3.53)

The results show that participation in extracurricular activities for any number of hours in 1991-1992 when most students were in 12th grade, significantly decreases the probability of dropping out, while working for any number of hours does not have any significant impact on the probability of dropping out.

For the 2011-2012 school year, the results are different. They show that while working less than 10 hours per week in this year seems to have no significant effect on the dropping out probability, working more than 10 hours increases this probability by 2.7%.

2.6 Conclusions and Future Work

In this paper, I examined the effect of participation in different after-school activities on academic outcomes. Unlike most of the previous research and following Hansen (2008), instead of focusing on the effects of working while in school, I also looked at extracurricular activities and their effects on students' GPAs for two surveys done 20 years apart which made it possible to look at the evolution of these effects through different generations. Since most likely these activities (both working and extracurricular activities) are endogenously chosen, I considered alternative approaches to address this issue. Descriptive statistics show that more than 70 percent of students participate in a form of extracurricular activity and in different years between 46 to 70 percent of students work while in school. The results from OLS estimation confirm that participation in after-school activities (including work), is endogenous. In this paper, two different approaches to deal with the endogeneity problem were proposed and implemented (proxy variables and fixed effect regressions). Participation in extracurricular activities is shown to be beneficial (for both cohorts) when using OLS estimations and adding math test scores as a proxy for unobserved ability that might impact the students' decisions regarding participation in after school activities. However, these positive effects become statistically insignificant in the fixed effect regressions for both cohorts which shows that there might be other unobserved characteristics in effect that can not be counted for with math test scores. Moreover, the two estimation methods suggest that working while in high school could be detrimental for students' GPAs. The negative effect is significant at older ages, specially in 1992 and 2012, and when running regressions on the intensity of working, the negative effect increases as the hours of work increase. Participation in extracurricular activities shows significant positive effect both when running OLS regressions and fixed effects.

Comparing the results of fixed effects regressions for the two cohorts suggest that in the span of 20 years, the negative effect of working in high school has increased. This may be the result of difference in the types of jobs students hold during high school in each cohort and this could be a subject for future research.

Chapter 3

Estimating the Technology of Youth Cognitive and Noncognitive Skill Production

3.1 Introduction

It is widely accepted that cognitive skills in children and youth are an important factor in explaining their social and economic success later in life (See Cawley, Heckman, & Vytlacil, 2001; Herrnstein & Murray, 2010; Murnane, Willett, & Levy, 1995). Further, a large body of interdisciplinary papers documents the important role of noncognitive skills on labour market outcomes, such as wages and education (See Borghans, Duckworth, Heckman, & Ter Weel, 2008; Heckman, Stixrud, & Urzua, 2006). There is a substantial body of empirical studies on the determinants of cognitive and noncognitive skills and their evolution but the majority focus on children (See Cunha & Heckman, 2007, 2008; Cunha, Heckman, & Schennach, 2010; Todd & Wolpin, 2003).

This paper estimates and identifies a model of the technology of skill formation, following the work done on child development, but focusing on teens. Building on the work done by Cunha and Heckman (2008), I jointly estimate the evolution of cognitive and noncognitive skills for high school students in the US. I model the self-production of skills as well as their impact on each other's production. The results show cross-production between cognitive and noncognitive skills. The analysis of cognitive and noncognitive skills, their role in forming each other and understanding the effectiveness of parental investment in shaping them, can help decide upon the type and timing of interventions needed for improving these skills and shed light on the family influence in this process.

Estimating skill production functions is challenging. There are two main issues researchers face: endogeneity of inputs into the production function and multiplicity of these inputs. If parental investments are affected by unobserved factors to improve their effectiveness, there would be endogeneity. For example, if a child is affected by an illness, which is unobserved to the econometrician but can be observed by the parents, and the parents see the illness as delaying the child's development, they may invest more than they would have otherwise in the child. This would create a negative correlation between parental investment and the unobserved error, and this may bias downward the impact of investments. There is a large body of literature that uses standard instrumental variables (IV) and fixed effect regressions (See Todd & Wolpin, 2003), to overcome the problem of endogeneity when estimating the skill production functions.

This paper adopts a methodology similar to that of Cunha and Heckman (2008) in identifying the technology of skill production. Specifically, I employ a dynamic factor model that incorporates covariance restrictions within linear systems to ensure proper identification. The idea involves modeling cognitive and noncognitive skills, alongside parental investments, as latent variables with low dimensions. To approximate these latent skills and investments, a range of measurements associated with skills and investments are employed. By having a sufficient number of measurements relative to the count of latent skills and investments, it becomes possible to discern the underlying factors responsible for skill development using cross-equation restrictions. The instruments are internally justified by assumptions made about the distribution of the error terms, following Cunha and Heckman (2008).

I assume the existence of two skill categories: cognitive and noncognitive. I investigate the impact of skill stocks at time t on the subsequent period's skill stocks at time $t+1$ and study both self-productivity, which pertains to the influence of cognitive skills on the production of cognitive skills and noncognitive skills on the production of noncognitive skills, as well as cross-productivity, which examines how noncognitive skills impact cognitive skill production and how cognitive skills affect the production of noncognitive skills in each period. I use a dynamic latent factor model where I proxy the vector of skills and parental investment by vectors of measurements on skills and investments.

I use data from two American surveys on high school students (National Education Longitudinal Study of 1988 and High School Longitudinal Study of 2009). I take test results on math, reading, science and history in the 1988 sample as measures of cognitive ability. These tests are repeated every two years. For the same cohort, I use scores in "locus of control" and "self-concept" as measures of noncognitive ability. Parental investments in this cohort are assumed to be in terms of both money and time spent on teenagers. For the 2009 sample, I take math score in the test which is taken in grade 9 and repeated at grade 12 as a measure of cognitive ability [1]. I also take GPA in math and GPA in science as measures of cognitive skills. Parental investment measures are again in terms of both money and time.

This paper contributes to the existing literature on the subject by estimating the cognitive and noncognitive skill production technologies for high school students instead of younger children. It also contributes to the literature by estimating the cognitive skill production technology for two cohorts of high school students, 20 years apart, and comparing the effects of different factors on the skill production process over time. Applying the methodology to the two surveys (NELS88 and HSLS09), I find that: (1) Both cognitive and noncognitive skills improve through teenage years (2) Parental inputs do affect the formation of these skills in teens (between 14 to 18 years old) and (3) the effect of different factors (such as parental education and parental investment) on the production of cognitive skills have increased between the early 1990s and early 2010s.

[1] There is no data on noncognitive skills in the 2009 cohort and that is the reason I only study the cognitive skill production process for this cohort

The paper proceeds as follows. Section 2 briefly reviews the literature on models of skill formation. Section 3 goes through the data used in this analysis. Section 4 presents the model. Section 5 discusses the empirical findings and section 6 concludes.

3.2 Literature Review

The set of skills acquired during younger ages plays an important role in the process of human capital formation. Many studies have found a strong causal relationship between the skills developed during young ages and later-life outcomes such as schooling, employment status, wages, and participation in risky behaviour (Almond & Currie, 2011; Borghans et al., 2008; Bowles, Gintis, & Osborne, 2001; Cunha, Heckman, Lochner, & Masterov, 2006; Dohmen, Falk, Huffman, & Sunde, 2010). Economics has contributed to the understanding of the skill development process by formulating production functions and estimating the effect of inputs at different stages of the life cycle (e.g., during early childhood and at school age).

A branch of this literature has found evidence of dynamic complementarity in the production of cognitive skills (Aizer & Cunha, 2012; Cunha & Heckman, 2008; Cunha et al., 2010). This means that skill attained at early stages in the life of children increases the effect of inputs in later stages. This finding is one of the key arguments to suggest the importance of early life investments to achieve a more able and productive adult population (Heckman & Mosso, 2014). The logic behind dynamic complementarity is that children who have grown up in more nurturing environments are better prepared to learn new things in later years.

There is another body of empirical work, however, that has found evidence that an increase in children's previous cognitive attainment can reduce the productivity of input and has labelled this as dynamic substitutability. Agostinelli and Wiswall (2016) and Garcıa and Gallegos (2017) estimated the productivity of parental investments using data from NLSY79 and the sample of children participating in the Infant Health and Development Program (IHDP), respectively. Contrary to the findings of Cunha et al. (2010), they both found that an increase in a child's prior stock of skills harms the productivity of parental investments. For example, Agostinelli and Wiswall (2016) found that the marginal productivity of early investments is higher for children with lower existing skills, suggesting the optimal targeting of interventions to disadvantaged children. They argue that this result is in contrast to the estimates from previous works in the literature since previously it was assumed that the technology of skill production is linear or CES and they believe that these technology specifications restrict the heterogeneity of the investment productivity by assuming that the marginal productivity of investment must be increasing (or constant) for a child's skills. Castro, Villacorta, et al. (2020) believe that learning is maximized when there is a match between the cognitive skill of the child and the complexity of the investment input. So for children with lower stocks of ability, some investments show dynamic substitutability.

3.2.1 Skill Development Process and Parental Investment

Cunha and Heckman (2008) employ estimation techniques to model the development of cognitive and noncognitive skills. They investigate how family environments influence the shaping of these skills during various phases of a child's life cycle. Their primary challenge involves identifying the mechanism responsible for skill development. To address endogeneity concerns related to inputs, they utilize a dynamic factor model for estimation. Endogeneity happens when factors unobserved to the econometrician are correlated with the independent variables. For example extra investment in a child who suffers from an illness that is not mentioned in the data. Multiplicity of inputs compared to the instruments can also cause problems, since choosing arbitrarily a limited number of variables from among multiple measures to proxy for certain inputs can affect the results. By assessing the impact of these factors on adult outcomes, they establish the scale of the factors. This approach eliminates the need to depend on test scores and their fluctuations, which lack a consistent metric. The study's findings indicate that parental investments tend to yield more significant improvements in noncognitive skills. Additionally, they observe a mutual promotion between noncognitive skills and the development of cognitive skills, whereby in the majority of their model specifications, the enhancement of cognitive skills does not appear to contribute to the development of noncognitive skills. Moreover, their analysis reveals that parental inputs exert distinct effects during various phases of a child's life cycle. Cognitive skills is more effected during the early stages (6 to 9 years old), while noncognitive skills are more impacted during later stages (8 to 12 years old).

Cunha et al. (2010) utilize data from CNLSY79 to construct and evaluate multi-stage production functions relating to children's cognitive and noncognitive skills. These skills are influenced by parental investments and background characteristics during distinct childhood phases. By estimating the elasticity of substitution between investments and skill stocks at each stage, they quantify the advantages of early as opposed to later investments in children. Their analysis focuses on children aged below 14 years.

They demonstrate a method to nonparametrically discern a wide range of production technologies utilizing nonlinear factor models that consider endogenous inputs. Leveraging this estimated technology, they establish the optimal targeting of interventions for children possessing different parental and inherent attributes. Their findings suggest that, in the production of cognitive skills, the substitutability of skills and investments diminishes during later life cycle stages, while it remains constant for noncognitive skills.

Helmers and Patnam (2011) utilize a dataset encompassing two cohorts of children aged between 1 and 12 from Andhra Pradesh, India. Their study delves into the factors that shape the production of children's cognitive and non-cognitive skills. The findings reveal indications of self-productivity within cognitive skills and note cross-productivity effects stemming from cognitive skills to noncognitive skills.

Furthermore, the research highlights the positive impact of parental investment on skill levels across all age groups. The exploration of additional determinants of these skills uncovers a connection between health status at age one and cognitive abilities at age five. They also establish that health status at age one can be influenced by parental care during both pregnancy and the initial year of life. Employing a latent factor model, they estimate the effects of these factors.

Aizer and Cunha (2012) study how endowments, investment and fertility interact to produce human capital in childhood. They begin by assuming that investments and existing human capital are complements in the production of later human capital (dynamic complementarity) and that parents invest more in children with higher abilities because of the complementarity between abilities and investments (static complementarity). For dynamic complementarity, they use an exogenous source of investment, the launch of Head Start in 1966, and estimate greater gains from preschool on the IQ of those with the higher stocks of early human capital, consistent with dynamic complementarity. For the static complementarity, they find that parents invest more in highly endowed children.

Coneus, Laucht, and Reuß (2012) examine the impact of parental investments on the development of cognitive and noncognitive skills during childhood, starting at birth until age 11, using data from the Mannheim Study of Children at Risk. They use measures of children's cognitive and noncognitive skills as well as measures of parental investments. The observed investments include parental health behaviour, playing and talking with the child, play materials, leisure activities and others. They estimate latent factor models to account for unobserved characteristics of children. They examine the skill development of girls and boys separately. They find a decreasing impact of parental investments on cognitive and mental skills over time until age 11, while it seems that emotional skills are unaffected by parental investments in childhood.

Del Boca, Flinn, and Wiswall (2014) estimate a model of the cognitive development process of children nested within a standard model of household behaviour. The household decides upon labour supply and provides time and money inputs into the production process of child quality during the period of development. Their results show that both parents' time inputs are important for the cognitive development of their children, particularly when the child is young but spending money is less productive in producing child quality. Counterfactual analysis shows that cash transfers to households with children have small impacts on child quality due to the relatively low impact of money investments on child outcomes and the fact that a significant portion of the transfer is spent on other household consumption. They use a dynamic production technology for child quality and a Cobb-Douglas specification of a household utility function and data from PSID-CDS on investments in children to estimate the parameters that characterize the child development process.

Agostinelli and Wiswall (2016) study the process of children's skill formation. They focus on the identification of this process. Using a dynamic latent factor structure, they provide new identification results which show some of the key identification trade-offs between restrictions on the skill production technology and the measurement relationships. One of their contributions is the development of empirically grounded restrictions on the measurement process that allow the identification of more general production technologies, including those exhibiting Hicks neutral total factor productivity (TFP) dynamics and free returns to scale. They then use their identification results and develop a sequential estimation algorithm for the joint dynamic process of latent investment and skill development. Using data from the United States, they estimate different versions of the skill formation model under various identifying assumptions. All their estimated models suggest that investments are particularly productive during early childhood. Moreover, they find that the marginal productivity of early investments is substantially higher for children with lower existing skills, suggesting the optimal targeting of interventions for disadvantaged children. When they compare their policy analysis results with cases where there are restrictions on the skill production function, they observe downward bias in the estimated policy effects in the restricted models, emphasizing the fact that the use of general technologies is important for accurate policy analysis.

Attanasio, Meghir, Nix, and Salvati (2017) use data from two developing countries, Ethiopia and Peru, to estimate the production functions of human capital from age 1 to age 15. They characterize the nature of persistence and dynamic complementarities between health and cognition. They also explore the implications of different functional form assumptions for the production functions. They find that more able and higher income parents invest more, particularly at younger ages when investments have the greatest impacts. These differences in investments by parental income led to large gaps in inequality by age 8 that persist through age 15. They estimate their model using a latent factor model to deal with endogeneity and measurement errors.

Attanasio, Cattan, Fitzsimons, Meghir, and Rubio-Codina (2020) examine the channels through which a randomized early childhood intervention in Colombia which was based on the Jamaican model of psychosocial stimulation via weekly home visits based on the curriculum now known as Reach-Up and Learn, also offering micronutrient supplementation, caused significant gains in cognitive and noncognitive skills among a sample of disadvantaged children ages 12 to 24 months at baseline. They estimate the determinants of parents' material and time investments in these children and evaluate the impact of treatment on such investments. They then estimate the production functions for cognitive and noncognitive skills. The results show that the program increases parental investments and emphasizes the importance of parental interventions at an early age.

Attanasio, Meghir, and Nix (2020) estimate production functions for cognitive skill and health for children of age 1-12 in India, based on the Young Lives Survey. The inputs into the production functions include parental background, prior child health, and child investments which are taken as endogenous. They estimate the model using a nonlinear factor model, based on multiple measurements for both inputs and child outcomes. Their results show an important effect of early health on a child cognitive development, which then becomes persistent. Parental investments affect cognitive skill production at all ages, but they are more effective for younger children. Investments also have an impact on health at early ages only.

Mitchell, Favara, Porter, and Sánchez (2020) estimate a dynamic model of multidimensional human capital development from childhood through adolescence and into early adulthood for a Peruvian cohort born in 1994. They use multiple measures of cognitive and noncognitive skills and a latent factor structure to estimate skill production functions between the ages of 8 and 22. They focus mostly on noncognitive skill development. They divided their data into four periods. In the last period, when individuals reach adulthood at age 22, they show that noncognitive skills can be separated into two distinct domains – social skills and task effectiveness skills – which develop differently with regard to time use and cross-productivity with cognition. They find that individuals with higher task effectiveness are less likely to have engaged in risky behaviour such as smoking, taking drugs, and engaging with gangs, which they take as a sign of future labour market outcomes.

In summary, there exists a rich literature in economics which studies the production of cognitive and noncognitive skills in youth using latent factor models. Most of these studies focus on children below the age of 14, although there are studies like Mitchell et al. (2020) who estimate skill production functions between the ages 8 to 22. The results of these studies show that cognitive and noncognitive skills improve throughout the life cycle of individuals. The effect of investment on the production of cognitive skills decreases with age but noncognitive skills show more malleability until later years.

3.3 Data

My analysis is based on data from two surveys, the National Education Longitudinal Survey of 1988 (NELS88) and the High School Longitudinal Survey of 2009 (HSLS09). NELS88 is a nationally representative sample of 27,394 young American males and females who were in 8th grade (13-16 years old) when they were first surveyed in 1988 while the HSLS09 consists of a nationally representative sample of 23,503 young males and females who were in 9th grade (13-17 years old) in 2009. For both cohorts, there is detailed information on family background and income, individual cognitive skills (measured by their scores in standardized tests), and GPAs and for NELS88 there is information on students' noncognitive ability as well. Also, there exists data on parental investment in their kids in both data sets. Interviews were conducted in 1988, 1990, 1992,1994 and 2000 for the first cohort and in 2009, 2011, 2012, 2016 and 2017 for the second cohort. In this paper, I use the first, second and third waves from the NELS88 and the first and second waves from the HSLS09.

I only keep individuals born in 1974 for the 1988 cohort and the ones born in 1995 for the 2009 cohort. This way I only estimate the model for students who are 14 at the time of the first wave of the surveys to be able to compare their cognitive and noncognitive test results at the same age [2]. After dropping students who were not 14 years old at the time of the first wave of the surveys, I was left with 7,583 individuals in the NELS88 and 11,767 individuals in the HSLS09. To be included in the sample, an individual respondent must also have completed the standardized test for cognitive skills in HSLS09 and for both cognitive and noncognitive skills in NELS88. Also, respondents with missing information on any of the measurement variables or any of the included family background variables were dropped. These selections reduced the sample to 3684 respondents for the 1988 cohort and 2471 respondents for the 2009 cohort. Some of the most important characteristics of my samples are found in Table 3.1 (devoted to summary statistics) and I compare my samples to the main samples of the NELS88 and the HSLS09 in Tables B.1 and B.2 in the Appendix. The comparison shows that in both cohorts, individuals in my samples have on average higher cognitive test scores and individuals in my 1988 sample have higher scores in both noncognitive measurements.

Cognitive test scores which follow item response theory (IRT) are increasing by age in both data sets. The Locus of control score decreases from age 14 to age 16 but increases at 18 again. I use this score as well as self-concept score as measures of noncognitive ability. Another observation is that the proportion of Mothers having some level of college education has increased from 54 percent in 1988 to 62 percent in 2009.

As measures for parental investment, I use monetary variables such as family income, educational expenses, money saved for college and time-use variables such as whether parents participate in parent-teacher organizations or volunteer at children's school. Complete lists of the measurement variables used for each cohort can be found in Tables 3.2 to 3.6.

3.3.1 Cognitive Skill Measurements

As measurements for individuals' cognitive ability, I use the following variables for each cohort: For the NELS88 I use the math and reading test results from standardized tests in 1988, 1990 and 1992 and for the HSLS09 I use the math test scores from standardized tests

[2] I kept individuals in these specific years so that I have test results at the same age for everyone, and follow individuals from as young of an age as the data allows.

Table 3.1: Descriptive Statistics (1988 Cohort)

Variable	NELS88 Mean	HSLS09 Mean
Math Test Score 1987 - 1988	39.95	-
Math Test Score 1989 - 1990	48.42	-
Math Test Score 1991 - 1992	53.05	-
Reading Test Score 1987 - 1988	29.79	-
Reading Test Score 1989 - 1990	33.86	-
Reading Test Score 1991 - 1992	36.21	-
Science Test Score 1987 - 1988	20.11	-
Science Test Score 1989 - 1990	23.27	-
Science Test Score 1991 - 1992	25.02	-
History Test Score 1987 - 1988	30.76	-
History Test Score 1989 - 1990	32.91	-
History Test Score 1991 - 1992	36.27	-
Locus of Control 1987 – 1988	0.1292	-
Locus of Control 1989 – 1990	0.1223	-
Locus of Control 1991 – 1992	0.1398	-
Self Concept 1987 - 1988	0.0145	-
Self Concept 1989 - 1990	-0.0050	-
Self Concept 1991 - 1992	-0.0016	-
Math Test Score 2008 - 2009	-	44.93
Math Test Score 2011 - 2012	-	62.27
Mother's education		
Below High School	10.60%	4.69%
High School Graduate	36.37%	33.43%
Some College	53.03%	61.88%
Black	7%	9%
Hispanic	8%	14%
Rural	32%	22%
Male	43%	46%
Sample Size	3684	2471

in 2009 and 2011. For the younger cohort I also use GPA in math and GPA in science in the 2011-2012 school year as measures for cognitive skill in 2012 and the math grade at the end of grade 8 as a measure of cognitive skill in 2009. The reason for different measures for the two cohorts is data restrictions.

The numbers presented in Tables 3.2 and 3.3 are estimates of the number of items that a person would have answered correctly if he or she had answered all of the items that appeared in any form of the test administered in these surveys. It is the probability of a correct answer on each item, summed over the total number of questions. The total number of questions in the mathematics question pool was 81 and in reading was 54 in NELS88. This number for HSLS09 was 118 items for the math test. The Bayesian Item Response Theory model lets us put all the scores in, say Mathematics, on the same vertical scale so that the scores, no matter the grade, can be interpreted in the same way. All the normal statistical operations that apply to any cognitive test score can be applied to the IRT-estimated number right. For example, a student's IRT-estimated number right in Mathematics in the tenth grade in NELS88 might be 41.3. That same student might have had an IRT-estimated number right of 35.3 in Math in the eighth grade and 44.5 in the twelfth grade. This particular student gained six points between the eighth and tenth grades (41.3 - 35.3 = 6) and 3.2 points between the tenth and twelfth grades (44.5 -41.3 = 3.2). The student's total gain over the four years was 9.2 points.

Table 3.2: Cognitive Skill Measurement Variables (1988 Cohort))

Measures	Range Values
Math Test Score 1987 - 1988	16.50 - 66.81
Math Test Score 1989 - 1990	17.23 - 72.76
Math Test Score 1991 - 1992	17.32 - 78.10
Reading Test Score 1987 - 1988	10.66 - 43.83
Reading Test Score 1989 - 1990	10.64 - 48.80
Reading Test Score 1991 - 1992	11.12 - 50.89

Table 3.3: Cognitive Skill Measurement Variables (2009 Cohort))

Measures at 14	Range Values
Math Test Score in 2009	15.97 - 69.93
Final grade in teen's most advanced 8th grade math course	0.25 - 4
Measures at 18	**Range Values**
Math Test Score in 2011	25.23 - 103.79
GPA in highest level math taken	0.25 - 4
GPA in highest level science taken	0.25 - 4

3.3.2 Noncognitive Skill Measurements

In the NELS88 data set, there is a set of fourteen variables that can be found in Table 3.4 below, which asks the students whether they feel they have control over the outside world and their lives or if it is the outside circumstances which control their lives. There are also questions about whether the teen feels good about themselves, if they feel they are worthy, etc. All these questions are answered by numbers 1 to 4 (4 for strongly agree and 1 for strongly disagree). Using these variables as inputs, two indices were created in the data, called locus of control and self-concept. I use these two variables in 1988, 1990 and 1992 as my measures of noncognitive ability. These are standard measures of noncognitive skills in the literature (See Anger & Schnitzlein, 2017; Blanden, Gregg, Macmillan, et al., 2006; Feinstein, 2000).

3.3.3 Parental Investment Measures

As measures for parental investment, I take variables presented in Tables 3.5 and 3.6 for the NELS88 and the HSLS09 respectively. My measures of parental investment are categorical. However, some of them, such as family income, money spent on tutoring or money saved for a teen's future education have several categories (between 7 to 15 categories), and others have less (2 to 4 categories).

Table 3.4: Noncognitive Skill Measurement Variables (1988 Cohort))

Measurements from 14 to 18
I feel good about myself
I don't have enough control over the direction my life is taking
In my life, good luck is more important than hard work for success
I feel I am a person of worth, the equal of other people
I am able to do things as well as most other people
Every time I try to get ahead, something or somebody stops me
My plans hardly ever work out, so planning only makes me unhappy
On the whole, I am satisfied with myself
I certainly feel useless at times
At times I think I am no good at all
When I make plans, I am almost certain I can make them work
I feel I do not have much to be proud of
Chance and luck are very important for what happens in my life
I feel emotionally empty most of the time

Table 3.5: Parental Investment Measurement Variables (1988 cohort)

Measures at 14	Range Values
Money Parents' set aside for child's future education	0 - \$22,738
Educational Expenses for the 1987 – 88 school year	0 - \$ 30,317
Measures at 16	
Family Income from all sources in 1990	\$1,390 - \$278,016
How often parents attend a school event in which child participated	0 - 2
How often parents attend school meetings	0 - 2
Measures at 18	
Educational expenses for the 1991 – 92 school year	0 - \$25,286
Money Parents set aside for teen's future education	0 - \$37,930

3.4 Methodology

I assume there are two kinds of skills: θ_t^C and θ_t^N, where θ_t^C is the cognitive skill and θ_t^N is the noncognitive skill. Let θ_t^I represent parental investment in a child's skills in period t, and $t \in \{1, ..., T\}$, where T is the number of periods of childhood.

Assume each child is born with initial stocks of skills $\theta_1' = (\theta_1^C, \theta_1^N)$ which are affected by family background. If I define $\theta_t' = (\theta_t^C, \theta_t^N)$ as the ability stock vector, the production technology for skill k during period t can be expressed as follows:

$$\theta_{t+1}^k = f_t^k(\theta_t', \theta_t^I). \tag{1}$$

Table 3.6: Parental Investment Measurement Variables (2009 cohort)

Measures at 14	Range Values
Whether parent attended parent-teacher conference since start of 2009 school year	0 - 1
Whether parent volunteered at teen's school since start of 2009 school year	0 - 1
Family income in 2009	\$ 11,997 - \$ 187,954
Measures at 17	**Range Values**
How often contacted teen's school since start of this school year	1 - 4
Family income in 2011	\$11,483 - \$179,902
Amount currently set aside for teenager's future educational needs	\$0 - \$45,932

for $k \in \{C, N\}$ and $t \in \{1, ..., T\}$. In this model, both skills produce next-period skills and are impacted by parental investment. Since the vector $\theta_t^{'}$ is an argument of equation (1), cognitive skills can improve the production of noncognitive skills and vice versa.

Identifying and estimating the technology described in (1) presents challenges. The inputs and outputs can only be approximated using proxy variables, leading to the concern of measurement errors within this model. Also, the inputs are endogenous because parents choose them. This paper estimates linear specifications of technology (1), similar to Cunha and Heckman (2008) to overcome these issues.

3.4.1 The Technology of Production of Cognitive and Noncognitive Skills

Following Cunha and Heckman, I study the development of both cognitive and noncognitive skills using the following equation system

$$\begin{pmatrix} \theta_{t+1}^C \\ \theta_{t+1}^N \end{pmatrix} = \begin{pmatrix} \beta_1^C & \beta_2^C \\ \beta_1^N & \beta_2^N \end{pmatrix} \begin{pmatrix} \theta_t^C \\ \theta_t^N \end{pmatrix} + \begin{pmatrix} \beta_3^C \\ \beta_3^N \end{pmatrix} \theta_t^I + \begin{pmatrix} \nu_t^C \\ \nu_t^N \end{pmatrix}. \tag{2}$$

I investigate the influence of cognitive and noncognitive skill stocks at time t on the stocks at time *t+1*. Additionally, I explore self-productivity, which refers to the impact of θ_t^C on θ_{t+1}^C and θ_t^N on θ_{t+1}^N, as well as cross-productivity, involving the effects of θ_t^N on θ_{t+1}^C and θ_t^C on θ_{t+1}^N, during each period. To achieve this, I employ a dynamic latent factor model, where I approximate $\theta_t' = (\theta_t^C, \theta_t^N, \theta_t^I)$ using measurement vectors for skills and investments.

Assume we have a measurement system that can be represented by a dynamic factor model:

$$Y_{j,t}^k = \mu_{j,t}^k + \alpha_{j,t}^k \theta_t^k + \epsilon_{j,t}^k.$$

for

$$j \in \{1, ..., m_t^k\}, k \in \{C, N, I\}.$$

Where m_t^k is the number of measurements on cognitive skills, noncognitive skills, or investments in period t; and where θ_t^k is a dynamic factor for components k, $k \in \{C, N, I\}$. $Var(\epsilon_{j,t}^k) = \sigma_{k,j,t}^2$, $Y_{j,t}^k$ is an available measurement of component k, $k \in \{C, N, I\}$, $\mu_{j,t}^k$ and $\alpha_{j,t}^k$ are the location and scale of the measurement system and $\epsilon_{j,t}^k$ is the measurement error. Due to the presence of multiple ability and investment measurements in the initial period of my dataset, I can identify the distribution of latent initial conditions. Additionally, I can identify the distribution for each $\theta^{\prime}{}^{t=(\theta_t^C, \theta_t^N, \theta_t^I)}$, as well as the interdependence between θ_t and $\theta_{t'}$, where $t \neq t'$.

As an illustration, consider θ_t^C as representing the cognitive skill stock of the agent during period t. However, θ_t^C is not directly observable; instead, a measurement vector denoted as $Y_{j,t}^C$ (where $j \in \{1, 2, ..., m_t^C\}$) is observed. We assume that:

$$Y_{j,t}^C = \mu_{j,t}^C + \alpha_{j,t}^C \theta_t^C + \epsilon_{j,t}^C. \tag{3}$$

Here, j belongs to the range $1, 2, ..., m_t^C$, and $\alpha_{1,t}^C$ is set as 1 for all t to establish a scale for the factors through normalization. The $\mu_{j,t}^C$ terms may have dependencies on additional variables.

There are similar equations for noncognitive skills and parental investment at age t, relating θ_t^N and θ_t^I to their measurement variables and the same normalization is done for these two equations ($\alpha_{1,t}^N = 1$ and $\alpha_{1,t}^I = 1$). The $\epsilon's$ are measurement errors.

I formulate the skill progression as a linear law of motion, represented by the equation:

$$\theta_{t+1}^k = \beta_0^k + \beta_1^k \theta_t^N + \beta_2^k \theta_t^C + \beta_3^k \theta_t^I + \nu_t^k. \tag{4}$$

Here, k belongs to the set $\{C, N\}$ and t takes values from 1 to T. The error term ν_t^k is independent across agents and remains independent over time for the same agents. However, it's important to note that ν_t^C and ν_t^N are allowed to exhibit free correlation. Furthermore, the assumption is made that the ν_t^k terms (where $k \in \{C, N\}$) are independent from the initial conditions (θ_1^C, θ_1^N).

The components of θ_t are permitted to exhibit unrestricted correlations for any given time point, as well as with any vector $\theta_{t'}$ where $t' \neq t$, and this interdependence can be accurately identified. I make the assumption that any variables in the $\mu_{j,t}^k$ are independent of $\theta_t, \epsilon_{j,t}^k$, and ν_t^k for $k \in \{C, N, I\}$ and $t \in \{1, ..., T\}$. The conditions under which the technology parameters are identified are explained in the following section.

3.4.2 Identification

The primary objective during the estimation process involves determining the collective distribution of $\{\theta_t^C, \theta_t^N, \theta_t^I\}_{t=1}^T$, alongside the distributions of $\{\nu_t^k\}_{t=1}^T$ and $\{\epsilon_{j,t}^k\}_{t=1}^T$ using a nonparametric approach. Additionally, the estimation aims to deduce the parameters $\{\alpha_{j,t}^k\}_{j=1}^{m_t^k}$ and $\{\beta_{j,t}^k\}_{j=1}^3$ for both $k \in \{C, N\}$ and $t \in \{1, ..., T\}$. Identification of the measurement means is straightforward under certain assumptions. We cannot separately identify the mean of the factor, $E(\theta_t^k)$, and the intercepts $\mu_{j,t}^k$. It is necessary either to normalize the intercept in one equation, $\mu_{1,t}^k = 0$ and identify $E(\theta_t^k)$ or to normalize $E(\theta_t^k) = 0$ and identify all intercepts $\mu_{j,t}^k$.

Assumptions on the Measurement Error for the Case of Two Measurements Per Latent Factor: $m_t^C = m_t^N = m_t^I = 2$

In this section, I explain the assumptions regarding measurement errors: I assume $\epsilon_{j,t}^k$ is mean zero and independent across agents and over time, it is also independent of the three latent factors, $(\theta_\tau^C, \theta_\tau^N, \theta_\tau^I)$ for all $\tau \in \{1, ..., T\}$; $j \in \{1, 2\}$; and $k \in \{C, N, I\}$. At the same time it is independent from $\epsilon_{i,t}^{l}$ for $i, j \in \{1, 2\}$ and $i \neq j$ for k=l; and is independent from $\epsilon_{i,t}^{l}$ for $i, j \in \{1, 2\}$; $k \neq l$, $k, l \in \{C, N, I\}$ and $t \in \{1, ..., T\}$.

Identification of the Factor Loadings for the Case of Two Measurements per Latent Factor

Since we observe $\{[Y_{j,t}^{k}]_{j=1}^{2}\}_{t=1}^{T}$ for every person, we can compute $Cov(Y_{1,t}^{k}, Y_{2,\tau}^{l})$ from the data for all t, τ and k,l pairs, where $t, \tau \in \{1, ...T\}; k, l \in \{C, N, I\}$. Consider, for example, measurements of cognitive skills. We set $\alpha_{1,t}^{C} = 1$ before. The left-hand side of each of the following equations is available in the data:

$$Cov(Y_{1,t}^{C}, Y_{1,t+1}^{C}) = Cov(\theta_{t}^{C}, \theta_{t+1}^{C}). \tag{5}$$

$$Cov(Y_{2,t}^{C}, Y_{1,t+1}^{C}) = \alpha_{2,t}^{C} Cov(\theta_{t}^{C}, \theta_{t+1}^{C}). \tag{6}$$

$$Cov(Y_{1,t}^{C}, Y_{2,t+1}^{C}) = \alpha_{2,t+1}^{C} Cov(\theta_{t}^{C}, \theta_{t+1}^{C}). \tag{7}$$

With this, I can determine $\alpha_{2,t}^{C}$ by calculating the ratio of Equation (6) to Equation (5), and $\alpha_{2,t+1}^{C}$ by obtaining the ratio of Equation (7) to Equation (5). In a similar manner, I can identify $\alpha_{j,t}^{k}$ for $t \in \{1, ..., T\}$ and $j \in \{1, 2\}$, subject to the normalizations $\alpha_{1,t}^{k} = 1$ for $k \in \{C, N, I\}$. This assumes that $\alpha_{2,t}^{k} \neq 0$ for $k \in \{C, N, I\}$ and $t \in \{1, ..., T\}$. If $\alpha_{2,t}^{k} = 0$, this would contravene the requirement that there are precisely $m_{t}^{k} = 2$ valid measurements for the factor θ_{t}^{k}.

The Identification of the Joint Distribution of $\{(\theta_{t}^{C}, \theta_{t}^{N}, \theta_{t}^{I})\}_{t=1}^{T}$.

After successfully identifying the parameters $\alpha_{1,t}^{k}$ and $\alpha_{2,t}^{k}$ (with the normalization $\alpha_{1,t}^{k} = 1$), I can reformulate equation (3) as follows:

$$\frac{Y^k_{j,t}}{\alpha^k_{j,t}} = \frac{\mu^k_{j,t}}{\alpha^k_{j,t}} + \theta^k_t + \frac{\epsilon^k_{j,t}}{\alpha^k_{j,t}},\ j \in \{1,2\} \text{ for } \alpha^k_{j,t} \neq 0,\ k \in \{C,N,I\};\ t \in \{1,...,T\}.$$

Now define

$$Y_j = \left\{ \left(\frac{Y^C_{j,t}}{\alpha^C_{j,t}}, \frac{Y^N_{j,t}}{\alpha^N_{j,t}}, \frac{Y^I_{j,t}}{\alpha^I_{j,t}} \right) \right\}_{t=1}^T \text{ for } j = 1,2;$$

$$\epsilon_j = \left\{ \left(\frac{\epsilon^C_{j,t}}{\alpha^C_{j,t}}, \frac{\epsilon^N_{j,t}}{\alpha^N_{j,t}}, \frac{\epsilon^I_{j,t}}{\alpha^I_{j,t}} \right) \right\}_{t=1}^T \text{ for } j = 1,2;$$

And,

$$\mu_j = \left\{ \left(\frac{\mu^C_{j,t}}{\alpha^C_{j,t}}, \frac{\mu^N_{j,t}}{\alpha^N_{j,t}}, \frac{\mu^I_{j,t}}{\alpha^I_{j,t}} \right) \right\}_{t=1}^T \text{ for } j = 1,2;$$

Let θ be the vector of all factors in all periods :

$$\theta = \{(\theta^C_t, \theta^N_t, \theta^I_t)\}_{t=1}^T.$$

We write the measurement equations as

$$Y_1 = \mu_1 + \theta + \epsilon_1.$$

$$Y_2 = \mu_2 + \theta + \epsilon_2.$$

Under the assumption that measurement error is classical, we can apply Kotlarski's Theorem (Kotlarski, 1967) and identify the joint distribution of θ as well as the distributions of $\epsilon^k_{j,t}$ for $j \in \{1,2,...,m^k_t\}$; $k \in \{C,N,I\}$ and $t \in \{1,2,...,T\}$.

For example, suppose that $\theta \sim N(0,\Sigma)$ and $\epsilon^k_{j,t} \sim N(0,\sigma^2_{k,j,t})$. We observe the vectors Y_1 and Y_2. Also, μ_1 and μ_2 are identified. As mentioned before, we can identify the factor loadings $\alpha^k_{j,t}$. To identify the distribution of the factors, we need to identify the variance-covariance matrix Σ. We can compute the variance of the factor θ^k_t from the covariance between $Y^k_{1,t}$ and $Y^k_{2,t}$:

$$Cov(Y^k_{1,t}, Y^k_{2,t}) = \alpha^k_{2,t} Var(\theta^k_t) \text{ for } k \in \{C, N, I\}.$$

The $\alpha^k_{2,t}$ is identified and the covariance on the left-hand side can be found from the data. The covariance of any two elements of θ can be computed as follows:

$$Cov(Y^k_{1,t}, Y^k_{2,\tau}) = Cov(\theta^k_t, \theta^l_\tau). \tag{8}$$

And

$$Cov(Y^k_{j,t}, Y^l_{k,\tau}) = \alpha^k_{j,t}\alpha^l_{k,\tau} Cov(\theta^k_t, \theta^l_\tau). \tag{9}$$

Where the coefficients $\alpha^k_{j,t}, \alpha^l_{k,\tau}$ are known by the previous argument. Since we know $Var(Y^k_{j,t}), \alpha^k_{j,t}$ and $Var(\theta^k_{j,t})$, we can identify $\sigma^2_{k,j,t}$ from these ingredients:

$$Var(Y^k_{j,t}) - (\alpha^k_{j,t})^2 Var(\theta^k_{j,t}) = \sigma^2_{k,j,t}, k \in \{C < N < I\}, t \in \{1, ..., T\}.$$

The Identification of the Technology Parameters Assuming Independence of ν

Let's consider the assumption that ν^k_t is independent of $(\theta^C_t, \theta^N_t, \theta^I_t)$. As an illustration, consider the law of motion for noncognitive skills:

$$\theta^N_{t+1} = \beta^N_0 + \beta^N_1\theta^N_t + \beta^N_2\theta^C_t + \beta^N_3\theta^I_t + \nu^N_t. \tag{10}$$

for $t \in 1, ..., T$. It is assumed that ν^N_t is serially independent, albeit potentially correlated with ν^C_t. I introduce the following definitions:

$$\tilde{Y}^N_{1,t+1} = Y^N_{1,t+1} - \mu^N_{1,t+1}.$$

$$\tilde{Y}^N_{1,t} = Y^N_{1,t} - \mu^N_{1,t}.$$

$$\tilde{Y}^C_{1,t} = Y^C_{1,t} - \mu^C_{1,t}.$$

$$\tilde{Y}^I_t = Y^I_t - \mu^I_t.$$

Substituting these measurement equations $\tilde{Y}^N_{1,t+1}, \tilde{Y}^N_{1,t}, \tilde{Y}^C_{1,t}, \tilde{Y}^I_t$ as proxies for $\theta^N_{t+1}, \theta^N_t, \theta^C_t, \theta^I_t$, respectively, yields:

$$\tilde{Y}^N_{1,t+1} = \beta^N_0 + \beta^N_1 \tilde{Y}^N_{1,t} + \beta^N_2 \tilde{Y}^C_{1,t} + \beta^N_3 \tilde{Y}^I_{1,t} + (\epsilon^N_{1,t+1} - \beta^N_{1,t}\epsilon^N_{1,t} - \beta^N_{2,t}\epsilon^C_{1,t} - \beta^N_{3,t}\epsilon^I_{1,t} + \nu^N_t). \quad (11)$$

When estimating equation (11) via least squares, the estimators for β^N_k (for $k \in 1, 2, 3$) would not be consistent due to the correlation between the regressors $\tilde{Y}^N_{1,t}, \tilde{Y}^C_{1,t}, \tilde{Y}^I_t$ and the error term:

$$\epsilon^N_{1,t+1} - \beta^N_{1,t}\epsilon^N_{1,t} - \beta^N_{2,t}\epsilon^C_{1,t} - \beta^N_{3,t}\epsilon^I_{1,t} + \nu^N_t.$$

However, it's possible to use $\tilde{Y}^N_{2,t}, \tilde{Y}^C_{2,t}, \tilde{Y}^I_{2,t}$ as instruments for $Y^N_{1,t}, Y^C_{1,t}, Y^I_{1,t}$, and apply a two-stage least squares method to estimate the parameters β^N_k for $k = 1, 2, 3$. The conditions on the factor loadings can be found in Madansky (1963) or Pudney (1982). The suggested instruments are also independent of ν^N_t. This process can be repeated for different periods. In this way, we can identify technologies for each period of the child's life cycle. We can perform a parallel analysis for the cognitive skill equation.

3.4.3 Sample Likelihood Function

In this part, I explain the likelihood and the basic estimation strategy for the model with classical measurement error and without serially correlated ν_t. During period t, define $m_t = m^N_t + m^C_t + m^I_t$, where m^N_t, m^C_t, and m^I_t represent the counts of measurements of the noncognitive, cognitive, and investment factors, respectively. The number of measurements is allowed to be period-specific. Let Y_t denote the $(m_t \times 1)$ vector

$$Y'_t = (Y^N_{1,t}, ..., Y^N_{m^N_t,t}, Y^C_{1,t}, ..., Y^C_{m^C_t,t}, Y^I_{1,t}, ..., Y^I_{m^I_t,t}).$$

In each period t, let $\theta_t' = (\theta_t^N, \theta_t^C, \theta_t^I)$. The matrix α_t, with dimensions $(m_t \times 3)$, is employed to represent the factor loadings:

$$\alpha_t = \begin{pmatrix} 1 & 0 & 0 \\ \vdots & \vdots & \vdots \\ \alpha^N_{m_t^N,t} & 0 & 0 \\ 0 & 1 & 0 \\ \vdots & \vdots & \vdots \\ 0 & \alpha^C_{m_t^C,t} & 0 \\ 0 & 0 & 1 \\ \vdots & \vdots & \vdots \\ 0 & 0 & \alpha^I_{m_t^I,t} \end{pmatrix}.$$

Consider ϵ_t as the $(m_t \times 1)$ vector representing disturbance terms, and let $K_t = Var(\epsilon_t)$, where K_t forms a $(m_t \times m_t)$ matrix. Utilizing this notation, we can express the observation equations during period t as follows:

$$Y_t = \alpha_t \theta_t + \epsilon_t. \tag{12}$$

Let G_t be a (3×3) matrix of coefficients. Let $\rho_{1,t}$ to $\rho_{5,t}$ contain the technology parameters for both cognitive and noncognitive factors:

$$\theta_{t+1} = G_t \theta_t + \rho_{1,t} Medu + \rho_{2,t} Hispanic + \rho_{3,t} Black + \rho_{4,t} Rural + \rho_{5,t} Male + \nu_t.$$

Here, the variable "Medu" denotes the mother's highest education level, acting as a proxy for the mother's cognitive skills, while the remaining variables are indicators: "Hispanic," "Black," "Rural," and "Male," representing race, urban/rural residence, and gender of the student, respectively. Furthermore, the vector ν_t encompasses the error terms in the technology equations, having dimensions (3×1). Let Q_t signify the variance of ν_t.

We assume that $\theta_1 | Medu, Hispanic, Black, Rural, Male \sim N(a_1, P_1)$. We also assume that $\epsilon_t \sim N(0, K_t)$ and $\nu_t \sim N(0, Q_t)$. Then given the normality assumption, together with linearity, it follows that $Y_1 \sim N(\mu_1, F_1)$ where:

$$\mu_1 = \alpha_1 a_1.$$

and

$$F_1 = \alpha_1 P \alpha_1' + K_1.$$

Now, I can apply the Kalman filtering procedure (for a detailed derivation, refer to Harvey (1990) and Durbin and Koopman (2012)). If we define:

$$Y^t = (Y_1, ..., Y_t).$$

then,

$$a_{t+1} = E(\theta_{t+1} | Medu, Hispanic, Black, Rural, Male, Y^t).$$

and,

$$P_{t+1} = Var(\theta_{t+1} | Medu, Hispanic, Black, Rural, Male, Y^t),$$

It can be shown straightforwardly that:

$$a_{t+1} = G_t a_t + G_t P_t \alpha_t' (\alpha_t P_t \alpha_t' + K_t)^{-1} (Y_t - \alpha_t a_t) + \rho_{1,t} Medu + \rho_{2,t} Hisp + \rho_{3,t} Black + \rho_{4,t} Rural + \rho_{5,t} Male.$$

And

$$P_{t+1} = G_t P_t'{}_{Gt} - G_t P_t \alpha_t' (\alpha_t P_t \alpha_t' + K_t)^{-1} \alpha_t P_t G_t + Q_t.$$

Consequently, employing the above equation, we deduce that:

$$Y_{t+1} | Medu, Hispanic, Black, Rural, Male, Y^t \sim N(\mu_t, F_t).$$

where $\mu_t = \alpha_t a_t$ and $F_t = \alpha_t P_t \alpha_t' + K_t$. Given our ability to observe factors such as maternal education, ethnicity, gender, and geographical location, we can break down the impact of individual i on the likelihood in the following manner:

$$f(Y_{i,T}, Y_{i,T-1}, ..., Y_{i,1}|Medu, Hispanic, Black, Rural, Male) =$$

$$f(Y_{i,1}|Medu, Hispanic, Black, Rural, Male) \prod_{t=2}^{T} f(Y_{i,t}|Medu, Hispanic, Black, Rural, Male, Y_i^{t-1}),$$

Here, Y_i^{t-1} signifies the history of Y_i leading up to period t-1. Assuming that the observations are independent and identically distributed (i.i.d) across children, the likelihood for the entire sample can be expressed as:

$$\prod_{i=1}^{n} f(Y_{i,T}, Y_{i,T-1}, ..., Y_{i,1}|Medu, Hispanic, Black, Rural, Male) =$$
$$\prod_{i=1}^{n} f(Y_{i,1}|.) \prod_{t=2}^{T} f(Y_{i,t}|Medu, Hispanic, Black, Rural, Male, Y_i^{t-1}).$$

3.5 Results

I report my empirical results in this section. The first set of results are from ordinary least squares regressions of measures of cognitive and noncognitive skills and parental investments at age 16 on the measures of skills and parental investment and some background characteristics at age 14. This is informative about the relationship between the cognitive and noncognitive test scores and parental investment measures at age 14 and the test scores and parental investment measures at age 16. These results are presented in Table 3.7.

The results show self-productivity and cross-productivity for the two skills. However, parental investment (to the extent that is measured by educational expenses) at age 14 does not affect the cognitive and noncognitive test results at age 16. We know that these results are probably biased due to the endogeneity issue.

The second set of results is from the 1988 cohort for which I estimate the skill production function for both cognitive and noncognitive skills using a dynamic latent factor model. There is information on cognitive and noncognitive measures for when the individuals are 14, 16 and 18 but I do not estimate the model for the duration between 16 and 18 to avoid dealing with high school dropouts and attrition problems in my sample. The results are

Table 3.7: OLS estimation of the technology equations

	Math at 16	Locus at 16	Family Income at 16
Math at 14	0.832**	0.117**	0.115**
	(93.98)	(7.46)	(8.09)
Locus at 14	0.037**	0.358**	0.022*
	(4.72)	(21.62)	(1.73)
Educational Expenses at 14	-0.0003	0.023	0.360**
	(-0.05)	(1.59)	(17.10)
Mother's Education	0.056**	0.032**	0.277**
	(6.53)	(2.10)	(18.44)
Hispanic	-0.072**	0.089	-0.194**
	(-2.39)	(1.54)	(-4.84)
Black	-0.123**	0.054	-0.341**
	(-3.99)	(0.83)	(-8.66)
Rural	-0.044**	-0.054*	-0.230**
	(-2.51)	(-1.70)	(-9.22)
Male	0.049**	-0.093**	0.005
	(3.02)	(-3.13)	(0.19)

presented in Table 3.8.

Results in Table 8 show that as expected, both cognitive and noncognitive skills have self productivity. Having more cognitive skills when the teenager is 14, increases both cognitive (self-productivity) and noncognitive skills (cross-productivity) at age 16. Noncognitive skills also show self productivity and there is also a statistically significant effect from noncognitive skills at age 14 on the production of cognitive skills at age 16. Parental Investment at age 14 increases noncognitive skills at age 16 but does not have any impact on the production of cognitive skills at that age.

Mother's highest level of education, which can be taken as a proxy for mother's ability, has no significant effect on noncognitive skill production between ages 14 and 16, but the effect on cognitive skill is positive and significant. After controlling for prior stocks of cognitive and noncognitive skills and parental investment and education, being from a racial minority has no statistically significant impact on the production of cognitive skills but the result shows that black and Hispanic teenagers have a higher noncognitive skill level at age 16 compared to the rest of the sample. Living in a rural area does not affect the cognitive and noncognitive skill production of teenagers and finally, gender does not show any impact

Table 3.8: Technology Equations:[a] between 14 to 16 years old, NELS88

	Cognitive at 16	Noncognitive at 16	Investment at 16
Cognitive skill at 14	0.972**	0.046**	-0.138**
	(26.65)	(2.05)	(-6.34)
Noncognitive skill at 14	0.087**	0.698**	0.038
	(3.05)	(26.57)	(1.39)
Parental Investment at 14	-0.002	0.086**	1.671**
	(-0.02)	(2.43)	(31.99)
Mother's Education	0.051**	0.023	0.245**
	(2.67)	(1.37)	(17.71)
Hispanic	-0.055	0.109**	-0.113**
	(-1.15)	(2.28)	(-2.37)
Black	-0.085	0.163**	-0.224**
	(-1.38)	(2.59)	(-4.04)
Rural	-0.019	-0.031	-0.099**
	(-0.86)	(-1.34)	(-4.37)
Male	0.002	-0.037	0.044
	(0.09)	(-1.46)	(1.03)

Consider $\theta_t' = (\theta_t^C, \theta_t^N, \theta_t^I)$ to represent the cognitive, non-cognitive, and investment dynamic factors, respectively. Let "Medu" symbolize maternal education, "Hispanic" and "Black" signify race indicators, "rural" denotes a binary variable indicating whether the student resides in an urban or rural area, and "male" represent a gender indicator. The technology equations can be expressed as follows:

$$\theta_{t+1} = \gamma_1^K \theta_t^C + \gamma_2^K \theta_t^N + \gamma_3^K \theta_t^I + \rho_{1,t} Medu + \rho_{2,t} Hispanic + \rho_{3,t} Black + \rho_{4,t} Rural + \rho_{5,t} Male + \nu_t$$

In this table, we show the estimated parameter values and t-statistics (in parentheses) of $\gamma_1^K, \gamma_2^K, \gamma_3^K, \rho_{1,t}, \rho_{2,t}, \rho_{3,t}, \rho_{4,t}$ and $\rho_{5,t}$ in columns 1 to 3.

on the production of cognitive and noncognitive skills.

The results for parental investments show that parents invest more in teens who have less cognitive skills but the stock of noncognitive skills does not impact the amount of time and money that parents invest in their teens. The results also show that parents who invest more in their children at 14, continue to do so at age 16. Mothers with higher levels of education, invest more in their children (both by spending time, and money). Parents of black and Hispanic teens invest less in their children. Also, in rural areas, parents invest less in their children. The results show that the gender of the teenager does not have any impact on the level of parental investment in the child.

These results are somewhat different than the results from the OLS regression. It seems that the OLS estimates of the self and cross productivities of the factors are downward-biased.

To see whether the effects from the dynamic factor model are different among males and females, I estimate the model once for males and a second time for females. The results are presented in Table 3.9.

Table 3.9: Technology Equations:[a] between 14 to 16 years old for males and females, NELS88

	Cognitive at 16		Noncognitive at 16		Investment at 16	
	male	female	male	female	male	female
Cognitive skill at 14	0.966**	1.011**	0.026	0.057**	-0.114**	-0.145**
	(29.86)	(38.40)	(1.23)	(2.71)	(-3.44)	(-4.70)
Noncognitive skill at 14	0.108**	0.088**	0.707**	0.760**	0.013	0.016
	(3.43)	(2.89)	(17.32)	(22.44)	(0.44)	(0.50)
Parental Investment at 14	-0.030	-0.092	0.111**	0.005	1.572**	1.712**
	(-0.43)	(-1.31)	(2.28)	(0.10)	(19.42)	(21.59)
Mother's Education	0.064**	0.055**	0.015	0.032	0.240**	0.249**
	(3.02)	(3.15)	(0.69)	(1.51)	(10.69)	(12.76)
Hispanic	-0.042	-0.061	0.110	0.074	-0.142**	-0.033
	(-0.58)	(-0.99)	(1.45)	(1.09)	(-2.02)	(-0.48)
Black	-0.172**	-0.044	0.101	0.163**	-0.219**	-0.193**
	(-1.99)	(-0.69)	(1.09)	(2.35)	(-2.14)	-2.73
Rural	-0.034	-0.018	-0.030	-0.043	-0.104**	-0.096**
	(-0.91)	(-0.58)	(-0.72)	(-1.28)	(-2.52)	(-2.65)

Consider $\theta_t' = (\theta_t^C, \theta_t^N, \theta_t^I)$ to represent the cognitive, noncognitive, and investment dynamic factors, respectively. Let "Medu" symbolize maternal education, "Hispanic" and "Black" signify race indicators, "rural" denote a binary variable indicating whether the student resides in an urban or rural area, and "male" represent a gender indicator. The technology equations can be expressed as follows:

$$\theta_{t+1} = \gamma_1^K \theta_t^C + \gamma_2^K \theta_t^N + \gamma_3^K \theta_t^I + \rho_{1,t} Medu + \rho_{2,t} Hispanic + \rho_{3,t} Black + \rho_{4,t} Rural + \nu_t$$

In this table we show the estimated parameter values and t-statistics (in parentheses) of $\gamma_1^K, \gamma_2^K, \gamma_3^K, \rho_{1,t}, \rho_{2,t}, \rho_{3,t}$ and $\rho_{4,t}$.

The results when I estimate the model for males and females separately are somewhat different from when I estimate the model for the whole sample. The new results still show self-productivity for the cognitive and noncognitive skills and cross productivity from noncognitive skills on cognitive skills for both males and females, but although there exists cross productivity from cognitive skills on noncognitive skills in females, the stock of cognitive skills at age 14 does not show any effect on noncognitive skill production at age 16 in males. The other difference between males and females is that parental investment does not have any effect on noncognitive skill production in females but has a significant impact on males.

I next estimate the model only for cognitive skills, for both 1988 and 2009 cohorts, since there is no information on noncognitive skills in the 2009 data set and since in the 2009 cohort I have only information for when the individuals are 14 and 17 years old, I could not avoid the issue of high school dropouts. For that reason, I only estimated the model for high school graduates (teens who eventually graduated from high school with a high school diploma). The results are presented in Table 3.10.

Table 3.10: Technology Equations:[a] between 14 to 18 years old, NELS88 and HSLS09

	Cognitive Skill at 18/17		Parental Investment at 18/17	
	NELS88	HSLS09	NELS88	HSLS09
Cognitive skill 14	0.964**	0.980**	-0.054**	0.069**
	(58.53)	(46.09)	(-3.14)	(5.40)
Investment 14	-0.029	0.216**	1.314**	0.993**
	(-1.30)	(2.06)	(48.55)	(12.74)
Mom Education	0.060**	0.054**	0.115**	0.275**
	(4.48)	(2.61)	(7.32)	(6.06)
Hispanic	-0.036	-0.068**	-0.110**	-0.127**
	(-0.77)	(-2.10)	(-2.26)	(-2.63)
Black	-0.151**	-0.067**	-0.062	-0.161*
	(-2.90)	(-3,27)	(-1.15)	(-1.68)
Rural	-0.065**	0.076**	-0.071**	-0.041**
	(-2.30)	(2.59)	(-3.04)	(-3.23)
Male	0.034	-0.071**	0.051**	0.076**
	(1.61)	(-4.51)	(2.84)	(1.97)

Consider $\theta_t' = (\theta_t^C, \theta_t^I)$ to represent the cognitive and investment dynamic factors, respectively. Use "Medu" to denote maternal education, "Hispanic" and "Black" as indicators for race, "rural" as a binary variable indicating the student's residency in an urban or rural area, and "male" as a gender indicator. The technology equations are expressed as:

$$\theta_{t+1} = \gamma_1^K \theta_t^C + \gamma_2^K \theta_t^I + \rho_{1,t} Medu + \rho_{2,t} Hispanic + \rho_{3,t} Black + \rho_{4,t} Rural + \rho_{5,t} Male + \nu_t$$

This table shows the estimated parameter values and t-statistics (in parentheses) of $\gamma_1^K, \gamma_2^K, \rho_{1,t}, \rho_{2,t},\ \rho_{3,t}, \rho_{4,t}$ and $\rho_{5,t}$.

The results for high school graduates in the 1988 cohort show that past levels of cognitive skills still have self-productivity. Parents' investment in earlier teenage years does not show a significant effect on cognitive skills productivity in later teen years in this cohort.

Mother's education level positively impacts the production of cognitive ability in youth in this sample between the ages of 14 to 18. Living in a rural area at age 14 negatively affects the production of cognitive skills at age 18. Being a black teenager, now that we do not control for noncognitive skills, shows a negative impact on the production of cognitive skills.

As for parental investment in 1988 cohort, the results show that parents invest more in teenagers with lower cognitive skill levels, higher-educated mothers invest more in their teenagers and parents who invest in their children in earlier years of adolescence, keep investing in them as they continue in high school. The results also show that parents of black and Hispanic teenagers, invest less in their kids and overall, parents invest more in their boys than their girls.

In the 2009 cohort, one can still observe a large amount of self-productivity for cognitive skills. Contrary to the 1988 cohort, in this younger cohort, parental investment at age 14 does show a positive effect on the production of cognitive skills at age 17. Mother's education positively affects the production of cognitive skills in teenagers in this cohort. Racial minorities (black and Hispanic teenagers) show less cognitive skill productivity between ages 14 to 17 in this setup. Living in a rural area in 2009, positively affected cognitive skill production and contrary to the 1988 cohort, in 2009, male students on average produced less cognitive skills compared to their female counterparts.

Parental investment in the 2009 cohort has a different pattern than the 1988 cohort. Parents in this cohort invest more in higher-ability teenagers (contrary to the older cohort) and Mother's education has twice as much impact on parental investment as the 1988 cohort. The rest of the variables have the same sign and impact on parental investment as in 1988.

Comparing the two cohorts, what's striking the most is the change in the sign of the effect of stock of cognitive ability at 14 on the parental investment in teens in later years, between the two cohorts. In the older cohort, the effect is negative, which means that parents invested more in their lower cognitively able kids. It could be that they are trying to help the less cognitively endowed teens to catch up. But in 2009, right after the great recession of 2008, the sign for the effect of cognitive ability on parental investment was positive. Meaning that the families in the younger cohort invest more in their more cognitively endowed teens. The last set of results is from estimating the dynamic factor model between 14 to 18 years of age, separately for males and females. The results are presented in Table 3.11.

When I estimate the model separately for males and females, for the 1988 cohort,

Table 3.11: Technology Equations:[a] for males and females between 14 to 18 years old, NELS88 and HSLS09

	Cognitive Skill at 18/17				Parental Investment at 18/17			
	NELS88		HSLS09		NELS88		HSLS09	
	Males	Females	Males	Females	Males	Females	Males	Females
Cognitive skill 14	1.024**	1.051**	0.987**	0.972**	-0.002	-0.024	0.035	0.085**
	(34.70)	(43.22)	(36.50)	(43.61)	(-0.06)	(-1.22)	(1.29)	(6.21)
Investment 14	-0.115*	-0.032	0.164**	0.267**	1.141**	1.135**	1.008**	0.976**
	(-1.94)	(-0.73)	(2.26)	(6.15)	(21.17)	(34.76)	(11.26)	(15.43)
Mom Education	0.061*	0.044**	0.056**	0.047*	0.135**	0.165**	0.276**	0.249**
	(1.83)	(2.41)	(2.12)	(1.74)	(4.19)	(10.71)	(10.89)	(15.85)
Hispanic	0.026	-0.036	-0.146**	-0.063**	-0.138*	-0.069	-0.066	-0.098**
	(0.28)	(-0.68)	(-2.31)	(-2.56)	(-1.93)	(-1.10)	(-1.19)	(-3.42)
Black	-0.247**	-0.046	-0.044	-0.128**	-0.096	-0.043	-0.221**	-0.084**
	(-2.70)	(-0.75)	(-0.61)	(-3.91)	(-1.21)	(-1.16)	(-2.76)	(-4.52)
Rural	-0.075	0.035	0.078	0.030	-0.069*	-0.066**	0.033	-0.039**
	(-1.44)	(-1.20)	(1.60)	(1.53)	(-1.74)	(-2.00)	(0.72)	(-2.73)

Consider $\theta_t' = (\theta_t^C, \theta_t^I)$ to denote the cognitive and investment dynamic factors, respectively. Use "Medu" to represent maternal education, and consider "Hispanic" and "Black" as indicators for race. Additionally, utilize the "rural" variable to indicate whether the student resides in a rural or urban area. The technology equations are formulated as follows:

$$\theta_{t+1} = \gamma_1^K \theta_t^C + \gamma_2^K \theta_t^I + \rho_{1,t} Medu + \rho_{2,t} Hispanic + \rho_{3,t} Black + \rho_{4,t} Rural + \nu_t$$

This table shows the estimated parameter values and t-statistics (in parentheses) of $\gamma_1^K, \gamma_2^K, \rho_{1,t}, \rho_{2,t}$, $\rho_{3,t}$ and $\rho_{4,t}$.

parental investment at age 14 shows a negative impact on males' cognitive skill production between the ages 14 and 18 (although the effect is only significant at a 10% significance level). This effect for the females in the same cohort is not statistically significant. However, the sign and significance of this effect for the 2009 cohort is different. The parental investment in 2009 shows a statistically significant positive impact on cognitive skill production between the ages 14 and 17 for both males and females.

Another observation from Table 11 is that in the older cohort, black males at 18 have less cognitive ability compared to males from other races. This effect is not significant for black females. However, the result has changed in 20 years and in 2009, the effect of being a black male on cognitive ability was insignificant. In this younger cohort, Hispanic males and females and black females have less cognitive ability productivity compared to others.

As for parental investment, in the 2009 cohort, it seems that families invested more in girls who are more cognitively able, but the effect of cognitive ability on parental investment for boys is insignificant in that cohort. In the 1990s, the stock of cognitive skills at age 14 did not have any significant impact on parental investments neither on males nor on females. One more observation is that parents in rural areas invested less in their kids compared to parents from urban areas, in the 1990s. In 2009, parents from rural areas invested less in their daughters. The effect of living in a rural area on parental investment in this cohort, for males, is zero. The last observation is that parents from minority groups (blacks and Hispanics) did not invest less in their kids, but in the 2009 cohort they did invest less in their children.

3.6 Conclusion

This study establishes and conducts estimation for a model centred on investing in the cognitive and noncognitive skills of children, utilizing a dynamic factor model framework. The foundation for this model draws from the research conducted by Cunha and Heckman (2008).

The empirical approach considers the fact that parental investments and outcomes are measured through proxies and that the inputs are endogenous. This approach enables me to use multiple proxy variables in my datasets that may be endogenous, without running out of valid instruments.

I reached the following major conclusions. (1) I find high levels of self and cross-productivity of cognitive and noncognitive skills. (2) I find that parental investment in teenage years does have a significant impact on the productivity of noncognitive skills but it does not show a significant effect on the production of cognitive skills (3) The effect of parental investments on the production of cognitive skills has increased between early 1990's and early 2010's. (4) The effect of parental investments on the production of skills differs between males and females.

This shows that investments in teens (either monetary or time) can affect skill development even in later years (specifically noncognitive skills). Given the results of my first paper, in which I showed that the effect of unobserved heterogeneity on educational outcomes has grown significantly in more recent decades, this could mean that investment in teenagers' noncognitive skills can potentially improve their educational outcomes which in turn can affect later life outcomes.

Appendix A

Appendix for Chapter 1

Table A.1: Parameter estimates of the dynamic model with income quartiles

	NELS88	HSLS09
Between age 16-18	Estimates	Estimates
Hispanic	-0.055	-0.001
	(0.07)	(0.03)
Black	0.418**	0.173**
	(0.09)	(0.07)
Number of Siblings	-0.086**	-0.093**
	(0.01)	(0.01)
Rural	0.206**	-0.011
	(0.05)	(0.03)
Male	0.129**	-0.278**
	(0.05)	(0.03)
Mother's Education	0.119**	0.125**
	(0.02)	(0.01)
Single Mother	-0.299**	-0.117**

	(0.06)	(0.03)
Cognitive Quartile 2	0.594**	0.350**
	(0.06)	(0.05)
Cognitive Quartile 3	0.990**	0.658**
	(0.06)	(0.04)
Cognitive Quartile 4	1.241**	1.014**
	(0.07)	(0.04)
Income Quartile 2	0.360**	0.251**
	(0.07)	(0.05)
Income Quartile 3	0.533**	0.515**
	(0.07)	(0.05)
Income Quartile 4	0.620**	0.725**
	(0.09)	(0.03)
Grade at age 16	0.150**	0.108**
	(0.01)	(0.004)
Between age 19-21	Estimates	Estimates
δ_0	-17.540**	-14.273**
	(0.67)	(0.38)
δ_1	13.463**	10.694**
	(0.58)	(0.08)
Hispanic	0.567**	0.00002
	(0.17)	(0.02)
Black	1.456**	0.373**
	(0.23)	(0.08)
Number of Siblings	-0.274**	-0.107**
	(0.04)	(0.07)
Rural	-0.153	-0.340**
	(0.13)	(0.03)

Male	-0.356**	-0.860**
	(0.11)	(0.07)
Mother's Education	0.530**	0.567**
	(0.05)	(0.11)
Single Mother	-0.451	-0.347**
	(0.15)	(0.12)
Cognitive Quartile 2	1.234**	0.926**
	(0.15)	(0.11)
Cognitive Quartile 3	2.601**	2.017**
	(0.17)	(0.15)
Cognitive Quartile 4	4.855**	3.533**
	(0.23)	(0.42)
Income Quartile 2	0.974**	0.420**
	(0.17)	(0.12)
Income Quartile 3	1.328**	1.248**
	(0.17)	(0.15)
Income Quartile 4	2.052**	1.859**
	(0.21)	(0.09)
Type 1	-0.363**	-0.458**
	(0.11)	(8.81)
Type 2	-14.637	-14.444*
	(39.41)	(7.95)
Type 3	-10.324	-13.472*
	(23.23)	(7.32)
Type 4	-2.922**	-12.021*
	(0.96)	(0.65)
Type 5	-1.329**	-1.246**
	(0.28)	(0.18)

Type 6	-0.386**	-1.460**
	(0.12)	(0.17)
Type 7	-14.950	-1.183**
	(47.97)	(0.13)
Type 8	-0.145	-0.825**
	(0.21)	(0.33)
Type 9	-32.378	-21.036
	(109.26)	(15.72)

Table A.2: Type proportions and location parameters for the model with income quartiles

	1988 Cohort		2009 Cohort	
Type	Location	Proportion	Location	Proportion
1	0.4	0.20	0.4	0.22
2	0.5	0.00	0.5	0.00
3	0.6	0.00	0.6	0.00
4	0.7	0.02	0.7	0.00
5	0.8	0.07	0.8	0.10
6	1.0	0.19	1.0	0.08
7	1.1	0.00	1.1	0.11
8	1.2	0.24	1.2	0.15
9	1.3	0.00	1.3	0.00
10	1.4	0.28	1.4	0.35

Table A.3: Parameter estimates of the dynamic model with income quartiles and cognitive factor

	NELS88	HSLS09
Between age 16-18	Estimates	Estimates
Hispanic	0.735**	-0.114**
	(0.10)	(0.05)
Black	1.416**	-0.025
	(0.13)	(0.08)
Number of Siblings	0.046**	-0.133**
	(0.02)	(0.01)
Rural	0.539**	-0.092
	(0.07)	(0.06)
Male	0.256**	-0.361**
	(0.05)	(0.04)
Mother's Education	-0.023	0.253**
	(0.02)	(0.02)
Single Mother	0.188	-0.179**
	(0.08)	(0.03)
Cognitive Factor	2.542**	1.264**
	(0.07)	(0.02)
Income Quartile 2	0.680**	0.454**
	(0.08)	(0.05)
Income Quartile 3	0.895**	0.852**
	(0.09)	(0.07)
Income Quartile 4	1.158**	1.225**
	(0.10)	(0.08)
Grade at age 16	0.177**	0.129**

	(0.01)	(0.004)
Between age 19-21	Estimates	Estimates
Hispanic	2.110**	-0.048
	(0.20)	(0.10)
Black	4.243**	-0.137
	(0.30)	(0.10)
Number of Siblings	-0.008	-0.103**
	(0.04)	(0.02)
Rural	0.413**	-0.385**
	(0.13)	(0.09)
Male	0.060	-0.738**
	(0.11)	(0.08)
Mother's Education	-0.052	1.013**
	(0.04)	(0.04)
Single Mother	0.636**	-0.379**
	(0.17)	(0.10)
Cognitive Factor	6.793**	4.220**
	(0.13)	(0.07)
Income Quartile 2	1.219**	0.933**
	(0.17)	(0.11)
Income Quartile 3	1.664**	1.757**
	(0.18)	(0.16)
Income Quartile 4	3.053**	2.471**
	(0.19)	(0.14)
Type 1	-6.266	6.101**
	(21.55)	(1.43)
Type 2	-5.719	-2.080**
	(20.00)	(0.58)

Type 3	-5.092	-3.610**
	(18.13)	(0.92)
Type 4	-4.280	-4.166**
	(15.59)	(1.03)
Type 5	-3.238	-4.217**
	(12.25)	(1.03)
Type 6	-1.735	-3.829**
	(7.14)	(0.93)
Type 7	0.559	-2.842**
	(0.97)	(0.69)
Type 8	4.582	-0.764**
	(15.87)	(0.18)
Type 9	14.920	5.453**
	(56.32)	(1.42)

Table A.4: Type proportions and location parameters for the model with income quartiles and the cognitive factor

	1988 Cohort		2009 Cohort	
Type	Location	Proportion	Location	Proportion
1	1.3	0.00	1.3	0.66
2	1.4	0.00	1.4	0.00
3	1.5	0.00	1.5	0.00
4	1.6	0.00	1.6	0.00
5	1.7	0.00	1.7	0.00
6	1.8	0.00	1.8	0.00
7	1.9	0.00	1.9	0.00
8	2.0	0.00	2.0	0.00
9	2.1	1.00	2.1	0.34
10	2.2	0.00	2.2	0.00

Table A.5: Parameter estimates of the dynamic model with income quartiles, cognitive factor and their interactions

	NELS88	HSLS09
Between age 16-18	Estimates	Estimates
Hispanic	0.673**	-0.066
	(0.09)	(0.04)
Black	1.298**	-0.001
	(0.12)	(0.06)
Number of Siblings	0.021	-0.119**
	(0.02)	(0.01)
Rural	0.538**	-0.067**
	(0.06)	(0.03)
Male	0.234**	-0.327**
	(0.06)	(0.04)
Mother's Education	-0.080	0.273**
	(0.02)	(0.01)
Single Mother	0.074	-0.136**
	(0.08)	(0.04)
Cognitive Factor	2.096**	1.385**
	(0.07)	(0.03)
Income Quartile 2	1.289**	0.372**
	(0.10)	(0.05)
Income Quartile 3	1.786**	0.749**
	(0.15)	(0.06)
Income Quartile 4	1.814**	1.198**
	(0.15)	(0.08)
Grade at age 16	0.176**	0.130**
	(0.01)	(0.004)

Quartile 2 x Cog factor	0.695**	-0.226**
	(0.11)	(0.05)
Quartile 3 x Cog factor	1.052**	-0.164**
	(0.15)	(0.05)
Quartile 4 x Cog factor	0.838**	-0.070
	(0.17)	(0.04)
Between age 19-21	Estimates	Estimates
Hispanic	2.105**	0.053
	(0.18)	(0.08)
Black	3.941**	-0.065
	(0.25)	(0.09)
Number of Siblings	-0.051	-0.070**
	(0.04)	(0.02)
Rural	0.458**	-0.346**
	(0.11)	(0.07)
Male	0.032	-0.666**
	(0.10)	(0.06)
Mother's Education	-0.051**	1.014**
	(0.03)	(0.04)
Single Mother	0.458**	-0.298**
	(0.16)	(0.07)
Cognitive Factor	5.696**	3.727**
	(0.17)	(0.09)
Income Quartile 2	1.963**	0.673**
	(0.16)	(0.10)
Income Quartile 3	2.683**	1.444**
	(0.16)	(0.12)
Income Quartile 4	4.761**	2.214**

	(0.28)	(0.13)
Quartile 2 x Cog factor	1.612**	0.567**
	(0.23)	(0.11)
Quartile 3 x Cog factor	2.064**	1.284**
	(0.19)	(0.25)
Quartile 4 x Cog factor	3.935**	1.010**
	(0.37)	(0.15)
Type 1	-3.231	10.902**
	(0.08)	(0.09)
Type 2	-3.031	2.205
	(2.11)	(18.40)
Type 3	-2.790	-1.009
	(2.08)	(3.57)
Type 4	-2.506	-2.791
	(2.04)	(1.65)
Type 5	-2.172	-3.699
	(1.99)	(4.57)
Type 6	-1.119	-3.895
	(1.91)	(6.10)
Type 7	-0.194	-3.445
	(1.51)	(6.46)
Type 8	1.580	-2.157
	(1.01)	(5.78)
Type 9	10.564**	10.260
	(0.36)	(3.71)

Table A.6: Type proportions and location parameters for the model with income quartiles and the cognitive factor and their interactions

	1988 Cohort		2009 Cohort	
Type	Location	Proportion	Location	Proportion
1	1.2	0.00	1.3	0.66
2	1.3	0.00	1.4	0.00
3	1.4	0.00	1.5	0.00
4	1.5	0.00	1.6	0.00
5	1.6	0.00	1.7	0.00
6	1.8	0.00	1.8	0.00
7	1.9	0.00	1.9	0.00
8	2.0	0.00	2.0	0.00
9	2.1	1.00	2.1	0.34
10	2.2	0.00	2.2	0.00

Appendix B

Appendix for Chapter 3

Table B.1: Comparison of NELS88 and the 1988 cohort sample

	NELS88	Sample 88
Math Test Score 1987 - 1988	37.33	39.95
Math Test Score 1989 - 1990	45.15	48.42
Math Test Score 1991 - 1992	49.98	53.05
Reading Test Score 1987 - 1988	27.89	29.79
Reading Test Score 1989 - 1990	31.56	33.86
Reading Test Score 1991 - 1992	34.16	36.21
Locus of Control 1987 – 1988	0.060	0.1292
Locus of Control 1989 – 1990	0.052	0.1223
Locus of Control 1991 – 1992	0.066	0.1398
Self Concept 1987 - 1988	-0.0041	0.0145
Self Concept 1989 - 1990	-0.0170	-0.0050
Self Concept 1991 - 1992	-0.0087	-0.0016
Mother's education		
Below High School	12.47%	10.60%
High School Graduate	33.35%	36.37%
Some College	54.18%	53.03%
Black	8%	7%
Hispanic	10%	8%
Rural	33%	32%
Male	48%	43%

Table B.2: Comparison of HSLS09 and the 2009 cohort sample

	HSLS09	Sample 09
Math Test Score 2008 - 2009	39.75	44.93
Math Test Score 2011 - 2012	55.27	62.27
Mother's education		
Below High School	6.08%	4.69%
High School Graduate	37.86%	33.43%
Some College	56.07%	61.88%
Black	9%	9%
Hispanic	14%	14%
Rural	23%	22%
Male	49%	46%

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