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The role of schools in the production of achievement*

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Abstract

What explains differences in pre-market factors? Three types of inputs are believed to determine the skills agents take to the labor market: ability, family inputs, and school inputs. Therefore to answer the previous question it is crucial to understand first the relative importance of each of those inputs. The literature on the production of achievement has not been able to provide an estimation that can take the three factors into account simultaneously at the student level. This paper intends to fill this gap by providing an estimation of the production function of achievement where both types of investments (families and schools) are considered in a framework where the inputs are allowed to be correlated with the unobserved term, ability to learn. I do that by using parents' saving for their child's postsecondary education to control for the unobserved component (i.e., ability to learn) in the production of skills. The estimates for the role of family inputs are in line with previous findings. Additionally, the estimates of school inputs show that they are also important for the formation of students' skills even after controlling for ability to learn.

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JEL Classification Codes: I21, J15

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1 Introduction

The literature on sources of inequality finds that "pre-market" factors (i.e., skills individuals acquire before entering the labor market) explain most of income inequality across individuals and between groups of individuals. In that vein, Neal and Johnson (1996) conclude that the observed wage gap between black and white students mostly disappears once we control for "pre-market" factors, measured by the Armed Forces Qualifying Test (AFQT). Likewise, Keane and Wolpin (1997, 2001) and Cameron and Heckman (1998) suggest that labor market outcomes are largely determined by skills acquired during the school-age period. More recently, Carneiro et al. (2005) find that factors determined outside of the market play a major role in accounting for minority-majority wage differentials in modern labor markets.

Several studies also document that the differences in test scores between blacks and whites widen with age in the school-age period.[1] However, the questions of how skills are acquired and evolve over time –i.e., their dynamics– and the importance of the three main inputs (ability, family inputs, and school inputs) still remain unsolved. The existing literature has not been able to provide an estimation of the production function of achievement that can take these three factors into account simultaneously at the student level.

This paper intends to fill this gap by providing an estimation of the production function of achievement where both types of investments (families and schools) are considered in a framework where the inputs are allowed to be correlated with the unobserved term, ability to learn. I do that by using parents' saving for their child's postsecondary education to control for the unobserved component (i.e., ability to learn) in the production of skills.[2] What makes this saving measure informative is the fact that parents decide it at the same time they choose the family and school inputs that will affect the observed test score (the current outcome). However, those savings will not affect the current outcome, but instead will affect future labor market outcomes through the choice to go to college. To the best of my knowledge, this is the first paper using savings for postsecondary education to recover a measure of parents' knowledge about their children's ability at the moment they make their input decision. More importantly, this identification strategy allows me to disentangle the effect of ability from the

[1] See, for example, Cunha and Heckman (2007a, 2007b), Currie and Duncan (1995), Blau and Currie (2006), and Fryer and Levitt (2004).

[2] With "ability to learn" I refer to the capacity to understand principles, truths, facts, or meanings; acquire knowledge, and apply it to practice; and the ability to comprehend.

effect of previous test scores on current test scores (see section 2.2). Identifying the effect of previous achievement on current achievement is important for analyzing the dynamics of educational policies.

Cunha (2007) and Cunha and Heckman (2007a, 2007b) had focused on the unobserved component of the production function (i.e., ability), while keeping school inputs implicit using the National Longitudinal Survey of Youth of 1979 Children and Young Adults (NLSY79-CS). Cunha (2007) estimates a production function using factor analysis in nonlinear settings and he recovers the unobserved distribution of initial skills and that of ability (or heterogeneity at later ages). Cunha and Heckman (2007a, 2007b) provide additional estimates of the production function focusing on the substitutability/complementarity between cognitive and noncognitive[3] skills at both a point in time and across time. One salient conclusion is that noncognitive skills foster the formation of cognitive skills, but not vice versa. Although these approaches try to overcome the endogeneity between inputs and the unobservable ability, they do not take into account school inputs. The current paper complements these results by providing estimates not only of family inputs, but also of the role of school inputs in the production of achievement.

Lui, Mroz, and van der Klaauw (2010) and Todd and Wolpin (2006) provide estimates of the production function of achievement merging NLSY79-CS with the Common Core Data (CCD). The CCD includes school variables at the county level as proxies of the true school inputs students receive. Using a value-added specification, Todd and Wolpin find that differences in the mother's ability (measured by AFQT) and home inputs explain large portions of test score gaps. In terms of the school characteristics, Todd and Wolpin find that their implied impact is very small compared with that of home inputs and the mother's AFQT. Lui, Mroz, and van der Klaauw (2010) estimate a structural model of migration and maternal employment decision. Their finding is that once parental responses are taken into account –that is, after parents adjust their location and the mother's labor supply decision– policy changes have only a minor impact on the child's test scores. Lui, Mroz, and van der Klaauw characterize schools by a set of average county-level school quality measures, which might not be the true school input the child is receiving because school quality varies greatly within counties. The current paper complements these results by providing estimates of family and

[3] Cognitive skills always refer to some measure of achievement, usually a test score, while noncognitive skills refer to "soft skills" such as motivation, persistence, time preference, and self control.

school inputs in the production of achievement using student level data for both types of inputs.

In this paper I provide an estimation of the production function of achievement that attempts to overcome the aforementioned problems. To that end I propose an estimation strategy that takes into account not only the dynamics of the accumulation of human capital, but also the choice of whether or not to attend schools. The idea of the identification strategy is as follows: Every period, parents observe their child's characteristics as well as other household characteristics (such as family income and parents' education) and decide whether to send the child to school, how many inputs to invest in that period, and whether or not to save for the child's postsecondary education (postsecondary education being significantly more expensive than elementary or high school education). This parental saving decision is used to recover the ability, or unobserved, component.[4] Therefore the identification strategy relies on the assumption that, conditional upon all the other observable variables affecting the saving decision, there exists a one-to-one mapping between savings and the unobserved term.

Another potential problem of the identification strategy is whether we are capturing "ability to learn" –i.e.., whether savings for postsecondary education is a good proxy for students' unobserved "ability to learn". To study that, in Section 4.3 I test for the presence of measurement error and a preference shifter, a students' fixed effect, in the saving function. I do that by incorporating the identification strategy for polynomials errors-in-variable model (Hausman, Newey, Ichimura, and Powell (1991) and Hausman, Newey and Powell (1995)) to the standard Olley and Pakes' algorithm.

I use the estimates of the production function of achievement to perform some counterfactual exercises. Following the literature, I focus on the black-white test score gap. In particular, I do an out of the sample exercise where I equalize the inputs of black students by the differential that white students in the sample are receiving. As opposed to what was found previously in the literature, the results suggest that schools are important in helping blacks catch up to their white counterparts.[5] Moreover, if inputs are altered only in 12th

[4] Cooley (2007) uses a similar invertibility condition to identify students' ability. She assumes that the portion of leisure time spent reading for fun is a function of students' ability. She then inverts this function to recover students' ability.

[5] One exception is a recent work by Hanushek and Rivkin (2009). They find that teacher and peer characteristics explain a substantial share of the widening of the black-white achievement gap between third and eighth grade. Also, using data from Israel, Goud, Lavy, and Paserman (2004) find evidence that early schooling environment has an important effect on high school dropout rates, repetition rates, and the passing rate on

grade, home and school inputs have similar impact on students' achievement. A policy that gives inputs in both 8th and 12th grade is found to be more effective than intervening only in 12th grade, a result that is consistent with the findings in Cunha (2007).

The order of the paper is as follows: Section 2 starts by pointing out the potential estimation problems by using OLS and presents the proposed estimation strategy. Section 3 describes the data and the variables used in the estimation, and Section 4 presents the empirical results. Finally, section 5 concludes.

2 A proposed framework to overcome estimation problems

The goal is to obtain consistent estimates of the following production function of achievement (ACH):

$$h_t^* = f_t(\underbrace{x_t}_{\text{family inputs}}, \underbrace{e_t}_{\text{school inputs}}, \underbrace{H}_{\text{parents' HC (education)}}, \underbrace{h_{t-1}}_{\text{previous ACH}}, \underbrace{\eta_t}_{\text{ability to learn}}) \quad (1)$$

In order to illustrate the estimation problems faced when trying to estimate the $f_t(.)$ function, consider the value-added specification.[6] That is, assume that the production function of achievement is:

$$h_t = \beta_0 + \beta_1 x_t + \beta_2 e_t + \beta_3 H_t + \beta_4 h_{t-1} + \eta_t + \varepsilon_t \quad (2)$$

where

$$h_t = h_t^* + \varepsilon_t$$

i.e., ε allows for ex-post productivity shocks.

If we want to estimate the production function of achievement, a natural starting point is Ordinary Least Squares (OLS). In the first subsection I describe the problems we face if we choose that strategy. Then the econometric strategy used in this paper is explained.

2.1 Basic problems of OLS estimates

To illustrate potential biases suppose that cognitive skills are produced according to the following technology:

matriculation exams necessary to enter college.

[6] This specification was first suggested by Hanushek (1986) and has been widely used in the education literature since then. Todd and Wolpin (2006) find, based on a RMSE criterion, the value-added specification is preferable to different reduced form specifications (contemporaneous, cumulative, child fixed effect, and sibling fixed effect) for the estimation of the production function.

$$h_t = \gamma_0 + \gamma_1(I_t) + \gamma_2 h_{t-1} + \underbrace{\eta_t + \varepsilon_t}_{\mu_t} \tag{3}$$

where I accounts for all inputs. The main problem of estimating such a technology by OLS is that, as econometricians, we do not observe students' ability. Thus the error term becomes $\mu_t = \eta_t + \varepsilon_t$. In this case, the OLS estimates are:

$$\widehat{\gamma}_1 = \gamma_1 + \underbrace{\frac{\widehat{\sigma}_{h,h}\widehat{\sigma}_{I,\eta}}{\widehat{\sigma}_{h,h}\widehat{\sigma}_{I,I} - \widehat{\sigma}^2_{I,h}}}_{\text{endogeneity bias}} - \underbrace{\frac{\widehat{\sigma}_{h,I}\widehat{\sigma}_{h,\eta}}{\widehat{\sigma}_{h,h}\widehat{\sigma}_{I,I} - \widehat{\sigma}^2_{I,h}}}_{\text{selection bias}}$$

$$\widehat{\gamma}_2 = \gamma_2 + \underbrace{\frac{\widehat{\sigma}_{I,I}\widehat{\sigma}_{h,\eta}}{\widehat{\sigma}_{h,h}\widehat{\sigma}_{I,I} - \widehat{\sigma}^2_{I,h}}}_{\text{selection bias}} - \underbrace{\frac{\widehat{\sigma}_{I,h}\widehat{\sigma}_{I,\eta}}{\widehat{\sigma}_{h,h}\widehat{\sigma}_{I,I} - \widehat{\sigma}^2_{I,h}}}_{\text{endogeneity bias}}$$

where $\widehat{\sigma}_{a,b}$ denote the sample covariance between a and b. This introduces two types of biases.

- Endogeneity bias: following the arguments in Todd and Wolpin (2003), any economic model of optimizing behavior predicts that the amount of resources allocated to a child will be responsive to the parent's perception of a child's ability. That is, parents choose inputs once they observe their child's ability, so we should expect $\sigma_{I,\eta}$ to be different from zero. It could be either positive or negative. On the one hand, it could happen that parents observing that their child is of high ability expect a higher return to their investment and so invest more in him. In this case a positive correlation would exist between children's ability to learn and the amount of inputs. On the other hand, it could be that parents who observe that their child is of low ability try to compensate for this by investing more inputs. This type of behavior would induce a negative sample correlation between student's ability to learn and the level of inputs.

- Selection bias: it will exist only if those children for whom it is profitable to attend school do not drop out. Therefore, the distribution of unobserved ability to learn in the sample is not the unconditional distribution, but the truncated distribution. If in this context children of higher ability are sent to school when they obtain lower values of previous test scores –i.e.., when they do poorly in school– because they can catch up later, the truncation point of the ability distribution will be negatively correlated with the previous test score. Hence, the sample average of ability will be decreasing in previous test scores.

The proposed identification strategy deals with both problems.

2.2 Econometric Strategy

The econometric relies in using a proxy variable approach. I assume that every school year parents observe the stock of human capital of their child, the child's ability to learn, and other household characteristics such as their family income. I assume as well that ability to learn follows a first-order Markov process, i.e., $\eta_{t+1} = g(\eta_t) + \xi_{t+1}$. This assumption is a departure from the literature. The literature on the production function of achievement usually assumes that ability to learn is a fixed effect. If ability to learn is a fixed effect we should find that $var(\xi_{t+1}) = 0$. In the empirical section, I search for the parameters of the distribution of ξ_{t+1} as part of the estimation to test this assumption.

Given the information parents have at the beginning of the period, if the child is old enough so that school attendance is no longer compulsory, parents can decide whether the child will go to school or drop out. After high school the child might attend a postsecondary institution, and parents can start saving for their child's postsecondary education in advance. The basic idea of the identification strategy is that parents make a saving decision to afford postsecondary education while their child is in middle and high school. They make this decision based on their family income, the child's achievement, and *the child's ability to learn*[7]; i.e.., :

$$s_t = s_t(FI_t, h_{t-1}, \eta_t) \tag{4}$$

In turn, the child's ability to learn will determine the likelihood of attending college, whether he/she will be given financial aid and which type of college he/she will be able to attend. Observing savings for postsecondary education allows me to recover the distribution of ability, as ability affects savings but savings does not affect the child's level of achievement in the current period.

Conditional on the other set of variables, we can invert this function to back out η_t:

$$\eta_t = f_t(FI_t, S_t, h_{t-1}) \tag{5}$$

Note that to be able to invert this function I rely on the assumption that, conditional on the other set of variables, there exists a continuous and monotonic choice of savings based on the

[7] This result can be obtained, for instance, from a simple overlapping generation model where parents care about the wellbeing of all their dinasty.

child's ability. Two cases might break this monotonicity assumption: (i) if savings depends only on family income or (ii) if savings depends only on parents' expectations about financial aid or some other way their children might find to pay the cost of postsecondary education.

Appendix A presents evidence from the sample on students in NELS88 that hints at a monotonic relation between savings for postsecondary education and measures of students performance. The empirical evidence suggests that financial aid is based on observables I considered in the estimation (family income, race, sex, student's performance on previous test scores). In most cases financial aid does not cover all postsecondary education expenses. Moreover, the quality component of postsecondary institutions could be a reason why we observe a higher net price of attendance for students that perform better on the SAT.

There are two other assumptions needed for the identification to be correct. There is a timing assumption of when the amount of savings is chosen and when it affects the production of human capital. In particular, it is necessary that savings does not affect the student's performance in the current period test. Because parents are asked about savings for postsecondary education only, the saving variable I am using should affect only future levels of human capital through the choice to attend college or not–and which postsecondary institution attend– but not the student's performance in the current period test.

A scalar unobservable assumption is necessary as well. This assumption limits the dimensionality of the econometric unobservables that affect student performance on the test. This assumption could be violated if savings for postsecondary education respond not only to family income, the student's previous test score, and the student's ability to learn, but also to other factors such as parental preference for education. If savings reponds to other unobservable factors, there is no longer a one-to-one mapping between savings for postsecondary education and students' ability to learn. In section 4.3 I investigate what happens when the scalar unobservable assumption is relaxed and present robustness exercises to test this assumption.

2.2.1 Estimation procedure

Replacing $\eta_t = f_t(H, s_t, h_{t-1})$ in the production function gives:

$$\begin{aligned} h_t &= \beta_0 + \beta_1 x_t + \beta_2 e_t + \beta_3 Y_t + \underbrace{\beta_4 h_{t-1} + f(FI_t, S_t, h_{t-1})}_{\phi(FI_t, S_t, h_{t-1})} + \varepsilon_t \\ &= \beta_1 x_t + \beta_2 e_t + \beta_3 Y_t + \phi(FI_t, S_t, h_{t-1}) + \varepsilon_t \end{aligned} \tag{6}$$

where Y_t accounts for all the control variables.

The first stage involves estimating (5) semiparametrically using a fourth order polynomial for $\phi(.)$, i.e.., treating $f(.)$ flexibly. As is noted by Ackerberg et al. (2006), treating $f(.)$ flexibly has important advantages. The saving function might be a complicated function that depends on the primitives of a model and might be the solution of a dynamic optimization problem.

Note that by assumption we are able to completely proxy for η_t and hence the residual in (5) represents factors that are not observed by parents when making their inputs decisions. Therefore we can get consistent estimates of β_1, β_2, and β_3. However, the non-parametric treatment of $f(.)$ does not allow one to separate the effect of h_{t-1} on the production of current human capital from its effect on the saving decision.

I identify the coeficient of h_{t-1} on the production of current human capital in two steps using information on students' dropout decisions. Note that from the estimates in the first stage we obtain:

$$\widehat{\eta}_t = \widehat{\phi}(H, S_t, h_{t-1}) - \beta_0 - \beta_4 h_{t-1} \tag{7}$$

that is, given a particular set of parameters (β_0, β_4) we can have an estimate of η_t.

Consider the expectation of human capital net of variable inputs in $t+1$ conditional on the information at the beginning of the period and not dropping out of school ($\chi_{t+1} = 1$):

$$\begin{aligned} & E\left[h_{t+1} - \widehat{\beta}_1 x_{t+1} - \widehat{\beta}_2 e_{t+1} - \beta_3 \widehat{Y}_{t+1} / \eta_t, \chi_{t+1} = 1\right] \\ = \;& \beta_0 + \beta_4 h_t + E\left[\eta_{t+1}/\eta_t, \chi_{t+1} = 1\right] \\ = \;& \beta_0 + \beta_4 h_t + E\left[\eta_{t+1}/\eta_t, \eta_{t+1} \geq \underline{\eta}_{t+1}(H, S_t, h_t)\right] \\ = \;& \beta_0 + \beta_4 h_t + g(\eta_t, \underline{\eta}_{t+1}) \end{aligned} \tag{8}$$

where $g(\eta_t, \underline{\eta}_{t+1}) = \int\limits_{\underline{\eta}_{t+1}} \eta_{t+1} \frac{F(d\eta_{t+1}/\eta_t)}{\int\limits_{\underline{\eta}_{t+1}} F(d\eta_{t+1}/\eta_t)}$. To go from the second to the third line we assume that the decision to not drop out of school depends on the child's ability to learn. Students above a certain threshold will continue in school. I assume that this threshold depends on his stock of achievement, the household characteristics, and the level of savings. All these variables will affect the probability of attending a postsecondary institution and therefore the probability of remaining in school.

In order to control for the selection, we need a measure of both: $\eta_t, \underline{\eta}_{t+1}$. I can get a measure of η_t from (7), but do not have a measure for $\underline{\eta}_{t+1}$. I use data on school dropouts to control for $\underline{\eta}_{t+1}$.[8] Given the previous assumptions, we can write the probability of not dropping out of school in period $t+1$ conditional on the information available in period t as:

$$\begin{aligned} & \Pr\left(\chi_{t+1}=1/\eta_t, \underline{\eta}_{t+1}(H,S_t,h_t)\right) \\ = \; & \Pr\left(\eta_{t+1} \geq \underline{\eta}_{t+1}(H,S_t,h_t)/\eta_t, \underline{\eta}_{t+1}(H,S_t,h_t)\right) \\ = \; & p_t\left(\eta_t, \underline{\eta}_{t+1}(H,S_t,h_t)\right) = P_t \end{aligned} \tag{9}$$

We can estimate (9) non-parametrically, using a fourth-order polynomial in (H, S_t, h_t) as the latent index. I assume that the *i.i.d.* shock received every period to the level of ability to learn follows a normal distribution. This implies that the probability of not dropping out of school follows a normal distribution as well.

Once we have an estimate for P_t, we can invert $\widehat{P}_t$ to get a measure of $\underline{\eta}_{t+1}$, i.e., $\underline{\eta}_{t+1}(\widehat{P}_t, \eta_t)$. The only condition we need for that inversion to be possible is that the density of η_{t+1} given η_t is positive in an area around $\underline{\eta}_{t+1}(H, S_t, h_t)$.

Substituting $\widehat{P}_t$ and $\widehat{\phi}$ in the production function we can obtain consistent estimates of the effect of lag test score:

$$\begin{aligned} & h_{t+1} - \widehat{\beta}_1 x_{t+1} - \widehat{\beta}_2 e_{t+1} - \beta_3 \widehat{Y}_{t+1} \\ = \; & \beta_0 + \beta_4 h_t + \eta_{t+1} + \varepsilon_{t+1} \\ = \; & \beta_0 + \beta_4 h_t + g(\eta_t, \underline{\eta}_{t+1}) + \xi_{t+1} + \varepsilon_{t+1} \\ = \; & \beta_0 + \beta_4 h_t + g\left(\widehat{\phi}(.) - \beta_0 - \beta_4 h_{t-1}, p_t^{-1}\left(\widehat{\phi}(.) - \beta_0 - \beta_4 h_{t-1}, P_t\right)\right) + \xi_{t+1} + \varepsilon_{t+1} \end{aligned}$$

To go from the second to the third line I use the assumption that the child's ability to learn receives an *i.i.d.* shock every period (ξ_t). The estimation is similar to the first stage where we use a fourth-order polynomial to approximate $g(.)$ and estimate it by NNLS. Note that because of the approximation for $g(.)$ β_0 cannot be identified. The identification of β_4 comes from comparing students with the same η_t and P_t but different h_{t-1}.

[8] This is an analogous strategy as the one suggested by Olley and Pakes (1996) to estimate production function of firms in the industrial organizational literature.

3 Data

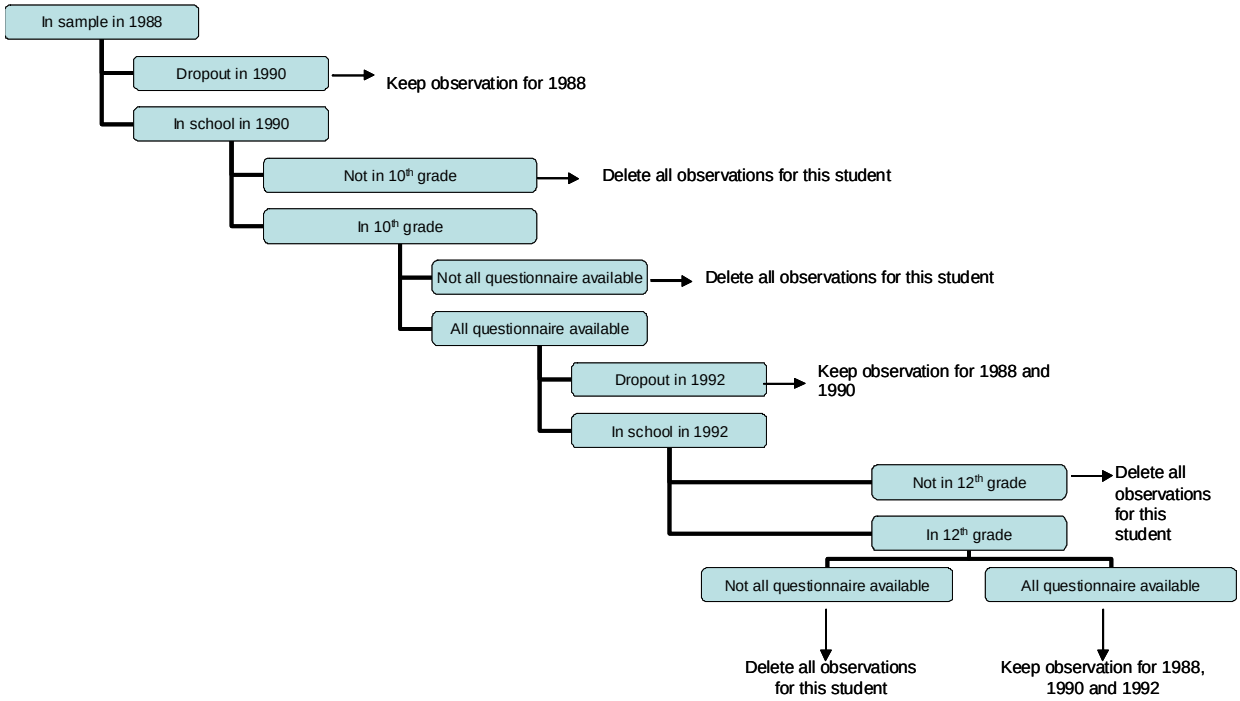
NELS:88 is a nationally representative sample of eighth graders who were first surveyed in the spring of 1988. The original sample employed a two-stage sampling design, selecting first a sample of schools and then a sample of students within these schools. In the first stage the sampling procedure set the probabilities of selection proportional to the estimated enrollment of eighth grade students. In the second stage 26 students were selected from each of those schools, 24 randomly and the other two among Hispanic and Asian Islander students. Along with the student survey, NELS:88 included surveys of parents, teachers, and school administrators. A sample of these respondents were resurveyed through four follow-ups in 1990, 1992, 1994, and 2000. Consequently, NELS:88 represents an integrated system of data that tracked students from middle school through secondary and postsecondary education, labor market experiences, and marriage and family formation. (See Appendix D for more details about the survey's sample and characteristics of each of the five collection years).

Sample From the 12,144 individuals in the NELS:88/2000 sample, I exclude those students that in 1988 belong to the "hearing impaired" sample; those students whose parent, teacher, or school administrator did not return the questionnaire; and those students with missing test scores.

In 1990 these students can be divided into three groups. For those students who in 1990 dropped out of school, only their eighth grade observation was kept in the sample. Among those students attending school in 1990, if the student was attending a different grade (that is, not in tenth grade) his complete history was deleted. If the student was in tenth grade and his teacher and school administrator answered the questionnaire, I kept the student in the sample. If any of these questionnaires are not available, the student's complete history was deleted.

I repeat the same procedure for the 1992 data. If the student dropped out, his observations while in school are kept in the data. For those in school, if the student was attending a grade different from twelfth grade, all his observations are deleted from the sample. If the student was attending twelfth grade, but either his parents, school administrator, or teacher did not complete the questionnaire, all the observations for that student were deleted. Finally, students in twelfth grade that had all relevant questionnaires completed are kept in the sample.

The following figure summarizes how I construct the sample:



The sample resulted in 6,293 students with answers for 1988. In the following years the sample shrinks due to dropouts. Consequently, the final sample is an unbalanced panel of students from 1988 to 1992.

Achievement Measures I use the percentile in the math test score distribution as a measure of students' achievement. All students in the sample took the same test provided by the Education Department. Table 1 in Appendix A shows mean values of the math percentile test score in different school grades. Previous literature has focused in both math and reading test scores, finding qualitatively similar results with both types of tests. Because only the math teacher can be observed across different grades in school, all the analysis is based on the math test score. The descriptive statistics in Table 1 are in line with other datasets: The gap between whites and blacks is important and it is increasing over students' lives. In eighth grade, the average black student tends to perform in the third decile, while the average white student is in percentile 52. At the end of the high-school period, the average white student

increases one percentile (i.e.., he performs in percentile 53); while the average black was in the same percentile as in eighth grade.

Home inputs NELS:88 includes a large set of questions related to family activities that might foster or discourage a student's test scores. Table 1 presents some of the measures used in the empirical analysis separated by race. All the measures show that whites are more likely to receive home inputs that foster achievement than blacks. For example, black children tend to read outside school on average 0.3 hours less than whites in eighth grade, increasing the difference to half an hour by twelfth grade. Blacks tend to watch on average more hours of TV than whites. While attending eighth grade a higher proportion of whites are sent to classes outside school (music, language, art) than whites, although this difference seems to narrow over time.

School inputs There are two types of school variables in NELS:88. One set of variables is observed at the school level, while the other corresponds directly to the class level and is answered by the teacher. Table 1 shows the average value for some of these variables. As in the case of home inputs, there are important differences across race. Black students attend on average schools with worst characteristics to foster their human capital accumulation than white students. For example, blacks are on average in classes with almost twice as many students receiving remedial classes than their white counterparts (12.21% versus 5.38%). On average blacks are also in classes in which the teacher spends a higher proportion of the class time maintaining the order. Both groups seems to have teachers with similar characteristics, in terms of wages, experience, and certification.

Parents characteristics One advantage of NELS:88 is that it provides information on both parents, mothers and fathers. Table 1 shows the proportion of parents with different years of education. Only 30% of black fathers attain some college or more, while almost 70% of white fathers do. Among mothers, differences are important, though not as extreme as with fathers. Having both parents' education is important to identify the home environment of the child. This seems important as, at least in this sample, there is evidence that mothers' education is not always the same as fathers' education (see Table 2, Appendix A). For example, for children whose mothers completed only high school, only 37% of the fathers had completed only high school, while 17% attended some college, 12% finished college, and 34% did not complete high school. Similar differences are observed for mothers with other schooling levels.

Savings for postsecondary education Savings parents make for postsecondary education are observed in every round of the survey where parents are surveyed. First, parents are asked whether they have taken any steps to ensure they have some money for they child's education after high school. For those that answer yes, they are asked how much money they have set aside. Table 1 shows that although there are big differences by race, the average saving-to-family income ratio is similar across races. In the empirical analysis, these differences jointly with other family and child characteristics provide the identification for heterogeneity across students.

4 Empirical Results

This section presents the estimates for the production function of achievement using the steps described in section 2.2. Two additional controls will be added to the ability function. The first one is race. Equation (5) assumes that there are not systematic differences in savings for postsecondary education across races, while the empirical evidence suggests that it might not be the case (see for example Oliver and Shapiro (2006)). I control for race in equation (5) to take care of this potential effect. Equation (5) assumes also that there are no gender differences. However, there is evidence that girls perform relatively poorer than boys in math test scores (see for example Todd and Wolpin (2006)). Without taking into account gender differences and given that all the analysis is based on math test scores, my estimation might underestimate girls' "ability to learn" and this difference would be captured by the sex coefficient. Therefore I control for gender in equation (5) as well. The identification of these coefficients is similar to the coefficient on the lag test score explained in Section 2.2.

I also need to search for the mean and standard deviation for the shock to ability to learn. For that, I added a loop on top of the algorithm described in Section 2.2. The starting point is to assume that the shock follows a standard normal distribution. Using the estimates I calculate the implied distribution for the shock and use this as the assumed distribution. I stop once the difference between the parameters of the assumed and implied distributions is sufficiently small.

I present first the estimates for a value-added production function using the proposed proxy variable approach (PV) and compared them with the standard OLS estimates for the same function. Then the estimates of a technology that allows for dynamic complementar-

ity/substitutability are presented.

In Section 4.2 I use these estimates to perform some counterfactual exercises. Following the literature, most of the counterfactual exercises focus on the black-white test achievement gap. In particular, I study how the actual gap would change by exogenously altering the inputs a group of students receive. Finally Section 4.3 presents robustness analysis for the assumption that savings for postsecondary education is a good proxy for students' ability to learn.

4.1 Estimates of the Production Function of Achievement

Table 3 presents the estimates for the production function under alternative specifications. The first column presents the estimates using OLS. Both home and school inputs are statistically significant for the production of achievement. The coefficient in the lag test score is statistically significant, positive, and less than one. This result is in line with previous literature. For example, Currier and Thomas (2000) find that the effect of Head Start tends to fade out over time when not followed up by later investments.

The second column shows the estimates when the proxy variable approach (PV) is used. The most important change with respect to the OLS estimates is in the effect of the lagged test score, with its coefficient increasing by more than eight standard deviations. Parents of children with larger stocks of human capital, h_{t-1}, should expect future higher returns for any level of their child's ability to learn. Hence, they will choose to send their children to school under lower realizations of their ability. Consequently, we should expect the truncation point of students' ability to learn to be decreasing in h_{t-1}; and, if the production function of achievement is increasing in h_{t-1}, this would imply a negative bias in the OLS estimate of its coefficient.[9]

For the home and school inputs, their coefficients are jointly statistically different under the PV estimations and the OLS estimation. Under the null hypothesis that they are equal, we get a χ^2 of 41.85 with a p-value of 0.0186. As was mentioned in Section 2.1, a priori the bias from the OLS estimates in the home and school inputs could go either way depending on whether the substitution or wealth effect dominates. In this sample there is evidence that the

[9] It could be argued that the change in the coefficient of the lag test score is due to measurement error. However, if the lag test score is instrumented with its lag, the coefficient of the lagged test score increases only by 3 standard deviations.

substitution effect dominates, as in most cases the impact of individual inputs goes down once we eliminate the endogeneity problem. If we increase all the inputs by one standard deviation, the OLS estimates predict an increase of 0.95 standard deviations of the average math test score, while the PV estimates predict that the average math test score would increase by 0.68 standard deviations.

In line with previous results in the literature there is evidence of sensitive periods. In this sense, the return to reading an extra hour decreases by 96% from 8th grade to 12th grade and it is not significant in the last case. In terms of the school inputs, the effect of the proportion of time that teachers use just to maintain order in the class decreases by 56%.

Table 4 presents the estimates of a technology that allows for dynamic complementarity/substitutability in the production of skills. In particular, I estimate the following production function:

$$h_t = \beta_0 + \beta_1 x_t + \beta_2 e_t + \beta_3 Y_t + \beta_4 h_{t-1} + \gamma h_{t-1}(\beta_1 x_t + \beta_2 e_t) + \eta_t + \varepsilon_t \tag{10}$$

Note that in order to make the estimation more tractable, all the inputs are compacted in an index, where each input's weight is their contribution to the production of achievement. This joint effect can be identified in the first stage of the algorithm, estimating this stage through NNLS, because current period inputs do not enter in the fourth-order polynomial used to approximate the unobservable component.

The estimates show that the effect of skills in the previous period changes significantly. Now β_4 is smaller and γ is positive and significant. From equation (10):

$$\frac{\partial h_t}{\partial h_{t-1}} = \beta_4 + \gamma(\beta_1 x_t + \beta_2 e_t) \tag{11}$$

that is, if investments are not followed by subsequent investments, achievement tends to fade out more rapidly. There is also strong evidence for dynamic complementarity: The return to current investment is 1.55 times higher the higher the stock of skills acquired in previous periods.

The estimated mean of the shock to ability to learn is 0.041 while the standard deviation is 0.258. These results support the assumption that ability to learn evolves over time rather than being a fixed effect as previously assumed in the literature.

4.2 Accounting Exercise

There exists a growing literature interested in understanding the production of skills because they are important determinants of labor market outcomes. To understand the effect of different inputs, in this section I use the estimates from Table 4 to study the impact of exogenously altering different types of inputs on students' achievement. Table 5 shows how the predicted black-white gap would change under different scenarios. The first exercise shows the test score gap if black students would receive, in addition, the differential of what white students receive. That is, for each input I regress the quantity of the input on family income, parental education, sex, race, and past achievement and a white dummy. I reassigned black students the actual amount they receive plus the differential that whites students receive. The estimated math test scores imply that home inputs would reduce the achievement gap by 15.6% while equalizing school inputs would do it by 9.2%. The second exercise is a "late remediation policy" where blacks receive additional inputs only in twelfth grade. The effect of both types of inputs in closing the gap decreases. School inputs would reduce the gap by 7.2% while home inputs would do it by 7.4%. That is, during the high school period the role of school inputs is closer to that of home inputs.

The estimates of the production function show that the lag test score is an important input. One important limitation of NELS:88 is that all the inputs information begins in eitghth grade, only after much has already had occurred in a child's life. To see how much of the gap is due to these differences in skills at the beginning of eighth grade, I calculate predicted tests scores using the estimated parameters and giving every student the maximum initial test score observed in the sample. In this case 16.4% of the gap would be closed, implying that initial conditions are important for future performance. This result is also in line with previous findings in the literature that suggest that early investments are more productive than later investments.

4.3 Robustness: Estimation problems when savings is a poor proxy of unobserved ability to learn

In order to estimate the contribution of home and school inputs to the production of achievement, I suggest that $s_{it} = f(\eta_{it}, controls)$ and assume that this is the true function generating savings. In a more general set up, it could be that $s_{it} = f(\eta_{it}, controls, \zeta_{it})$, where ζ_{it} is an

additional component, unobserved by the econometrician. For example ζ_{it} could be measurement error. Alternatively, we could think that ζ_{it} is a variable that affects the true savings function, like parents' generosity towards their children. In this section I study whether the inclusion of such a variable could bias the results and how I could solve this issue.[10]

To derive the estimation problems we would face, assume the production function of achievement is governed by the following technology:

$$h_{it} = \gamma_0 + \gamma_1 I_{it} + \nu_{it} \tag{12}$$

where $\nu_{it} = \eta_{it} + \varepsilon_{it}$, η_{it} is ability to learn and ε_{it} represents some idiosyncratic shock to the production of achievement or just classical measurement error in test scores. Without loss of generality, assume both components have mean zero. As mentioned in Section 2.1, any economic model of optimizing behavior would predict that the amount of resources allocated to a child will be responsive to the parent's perception of a child's ability –that is, $cov(I_{it}, \eta_{it}) \neq 0$. To simplify the analysis assume that $cov(I_{it}, \varepsilon_{it}) = 0$.

For illustration lets set aside the control variables considered in the saving function; that is, suppose that in addition to ζ_{it} the only determinant of savings is ability to learn, and consider the simple case where the previous function is linear; i.e.,

$$s_{it} = \beta \eta_{it} + \zeta_{it} \tag{13}$$

If this is the true relation between savings and ability to learn, then can we use savings to solve the endogeneity and selection problems of the OLS estimation? Yes. In fact it can be shown (see Appendix C) that the bias using savings as a proxy variable for unobserved ability to learn can never be higher than the bias of the OLS estimates and it equals

$$E(\widehat{\gamma}_1 - \gamma_1) = \frac{-\sigma_{s_t\mu}\frac{\sigma_{is_t}}{\sigma_{ii}}}{\left[\sigma_{s_ts_t} - \frac{\sigma_{is_t}^2}{\sigma_{ii}}\right]} = \frac{\sigma_\zeta^2}{\left[\beta^2\sigma_\eta^2\left(1 - r_{i\eta_{it}}^2\right) + \sigma_\zeta^2\right]} E(\widehat{\gamma}_1^{OLS} - \gamma_1)$$

[10] In this section I study what would be the estimates if the saving function depends on unobservable characteristics other than ability to learn. It could be argued that parents could choose other types of investments in their child's achievement. Moving to a neighborhood with better schools or sending their child to private school could be an alternative. However, the estimates do not change significantly when the sample is restricted either to those students that do not change neighborhood or to students attending public schools. Tables 7 and 8 in the Appendix show how much of the gap family and school inputs would close under these two restricted samples.

The extent of this bias will depend on the correlation between the regressors of interest (home and school inputs) and the proxy variable (σ_{is_t}) and the correlation between the proxy variable and the error term ($\sigma_{s_t\mu}$).

To study whether the estimators are consistent, we need additional information. Given that the panel gives only two saving observations per student, I will take into account two cases for the stochastic component for which I can obtain identification in the sample.

4.3.1 Identification under alternative specifications

Measurement error Suppose that the unobserved term ς_{it} is pure measurement error. That is, assume it is *i.i.d.* across individuals and time, so that $cov(\varsigma_{it}, \varsigma_{it-1}) = 0$. In this case we can use savings from a different period, say $s_{i,t-1}$, to instrument for s_{it}, as in this case $cov(s_{i,t-1}, \varsigma_{it}) = 0$. This procedure is called "multiple indicator solution". To see why the bias vanishes, consider again

$$E(\widehat{\gamma}_1 - \gamma_1) = \frac{-\sigma_{s_t\mu}\sigma_{is_t}}{\left[\sigma_{ii}\sigma_{s_ts_t} - \sigma^2_{is_t}\right]}$$

if we use $s_{i,t-1}$ to predict $s_{i,t}$ ($s_{i,t} = \theta s_{i,t-1} + \xi_{it}$), then:

$$\sigma_{s_t\mu} = E\left[\sum \widehat{\theta} s_{i,t-1}\mu\right] = E\left[\sum \widehat{\theta} s_{i,t-1}\left(\varepsilon_{it} - \frac{1}{\beta}\zeta_{it}\right)\right]$$

where we use $\mu_{it} = \varepsilon_{it} - \frac{1}{\beta}\zeta_{it}$ as defined in (14) Appendix C. It follows that

$$\sigma_{s_t\mu} = E\left[\widehat{\theta}\sum s_{i,t-1}\varepsilon_{it} - \frac{\widehat{\theta}}{\beta}\sum s_{i,t-1}\zeta_{it}\right] = 0$$

given that $cov(s_{i,t-1}, \varsigma_{it}) = 0$, which implies $E(\widehat{\gamma}_1 - \gamma_1) = 0$.

To test the presence of measurement error in the saving function we can run the same set of regressions as in section 4.1 but instrumenting the current period saving with savings in a different period. The problem in this case is that in the estimation of Section 4.1 a fourth-order polynomial expansion of parental savings for postsecondary education is used. That is, we have a polynomial errors-in-variables model. Identification in this case is still possible, but not by using a linear projection in the first stage. The problem is that powers of the measurement error get interacted with the coefficients, and to identify them we need to identify those moments of the error term as well. If a linear projection of the type of $s_{i,t} = \theta s_{i,t-1} + \xi_{it}$ is used, the estimated coefficients would be a linear combination of the true coefficients and different

moments of the measurement error term. Hausman, Newey, Ichimura, and Powell (1991) and Hausman, Newey, and Powell (1995) proposed an identification strategy for polynomial errors in variable models, and that is the one I follow in this case. To obtain identification, I combine a linear projection in the first-stage ith-moment condition between the dependent variable and the instrument, and the variable measured with error and the instrument (see the cited literature for details).

Preference Shifter Suppose ς_{it} is persistent over time for each student; i.e.., $\varsigma_{it} = \varsigma_{it-1} = \varsigma_i$. This scenario could arise if the unobserved component of savings is due to parents' preference parameter, such as parents' generosity toward their children. In this case, instrumenting current period savings with savings in a different period would not eliminate the bias as $cov(s_{i,t-1}, \varsigma_i) \neq 0$. Instead, the change in savings $s_{i,t} - s_{i,t-1} = \beta(\eta_{it} - \eta_{it-1})$ does. Change in savings is correlated with savings, but not with ς_i, and so it allows us to obtain consistent estimates of our parameters of interest.

4.3.2 Estimation Results

Both instruments require that we observe two savings observations for each student; therefore all the estimations in this section include only the balance panel of students that do not drop out from school between 8th grade and 12th grade. Consequently I cannot estimate the survival probabilities needed to identify the coefficients in the third stage of the algorithm. To be able to run the third stage, I use each student's survival probabilities estimated from the unbalance panel. I use these probabilities for the three measures of savings: current period saving (the suggested measure), savings in a different period (measurement error case), and change in savings (preference shifter case). I reestimate the OLS coefficients for this balance panel as well.

Using the estimates of each alternative specification I compute how much of the black-white gap could be closed by giving black students the differential of what white students receive on top of what they received. Table 6 presents the results under the alternative specifications, the original OLS, and PV value-added specifications and the two PV estimations using each instrument. In comparison with its OLS alternative, the PV estimator using current period saving does much better. The PV estimator predicts that both types of inputs, home and school, would close the gap by a smaller fraction than what OLS predicts. In both cases the

PV prediction is closer to what the instrument for each extreme case predicts.

5 Conclusion

The existing literature on sources of inequality find that "pre-market" factors, skills individuals acquire before entering the labor market, explain most of income inequality across individuals and between groups of individuals. But what explains differences in pre-market factors? A growing literature in economics tries to provide an answer to this question by studying children's performance in test scores . This paper contributes to that literature by proposing an identification strategy that accommodates usual endogeneity problems in the choice of inputs and whether to attend schools or not and applying it to a very suitable dataset for this problem: NELS:88. NELS:88 provides information of both home and school inputs at the student level as well as parents' saving for their child's postsecondary education that I use to control for the unobserved component (i.e., ability to learn) in the production of skills. This allows me to recover the parameters of interest in the production function of achievement: the effect of period-by-period investment as well as the impact of the achievement acquired in previous periods. The estimates show that in fact the most significant change from applying the proposed strategy rather than an OLS estimation occurs in the lag test score. Additionally, I find evidence that these savings are not a poor proxy for students' unobserved ability to learn.

The estimates for the role of family inputs are in line with previous findings, they foster students achievement, and there exists sensitive periods. However, the estimates of school inputs show that, contrary to what has been found in the literature, they are important for the formation of students' skills and they seem to be as important as home inputs if late remediation policies are considered.

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6 Appendix A: Savings, students' performance and family income

In order to be able to invert equation (4) we need a monotonic relation between savings for postsecondary education and ability to learn. Two cases might break this monotonicity assumption: if savings depend only on family income or if savings depend only on parents' expectations about financial aid or some other way their children might find to face the cost of postsecondary education.

In the first case, if savings depend only on family income, then we should expect richer families to save more independently of their children's level of achievement. If this is the case, conditional on family income there will be no relation between savings and achievement. Figure 1 shows the relation between students performance in math test score and savings for each quartile of family income. It can be observed that parents of children that do better tend to save more for their child's postsecondary education within each income quartile. Thus, there is evidence that conditional on family income there exists a relation between the saving decision and students' achievement. The data also shows that savings are not completely explained by the observables included in the saving functions Figure 2 presents the distribution of savings conditional on family income, race, sex, past achievement.

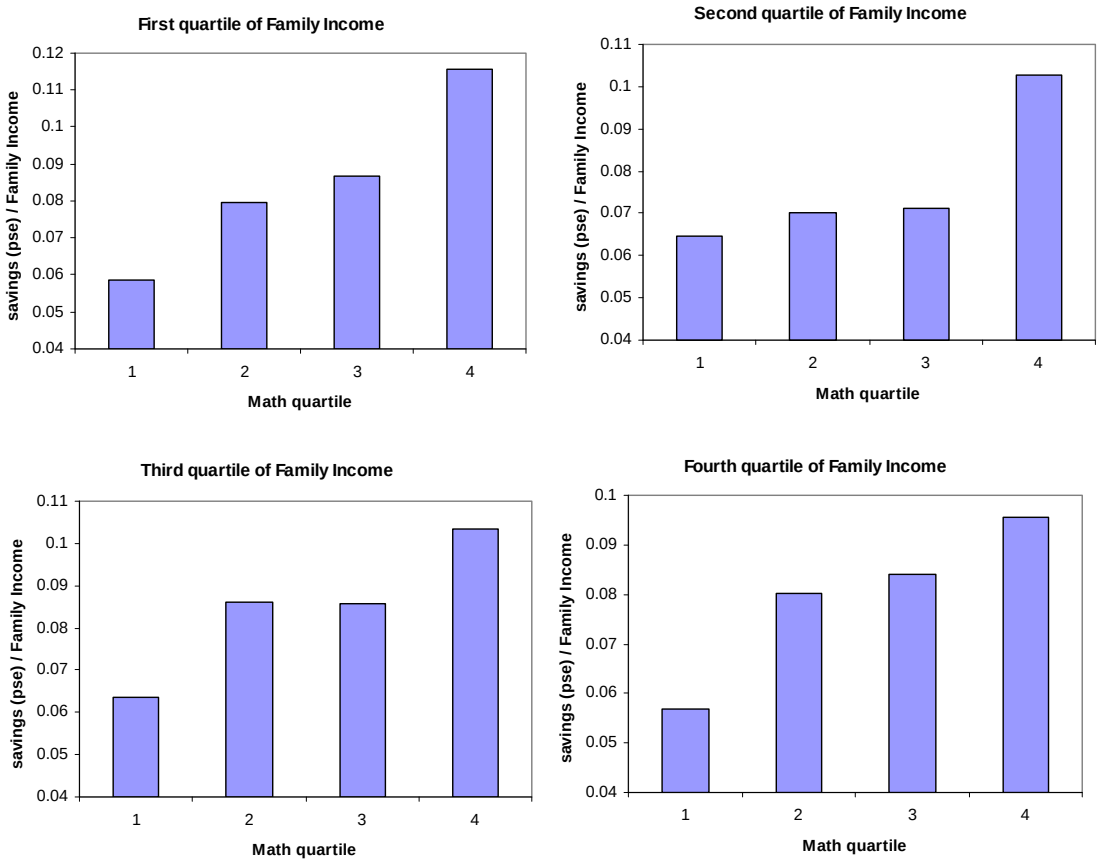

Figure 1: Math test score and savings by quartile of family income.

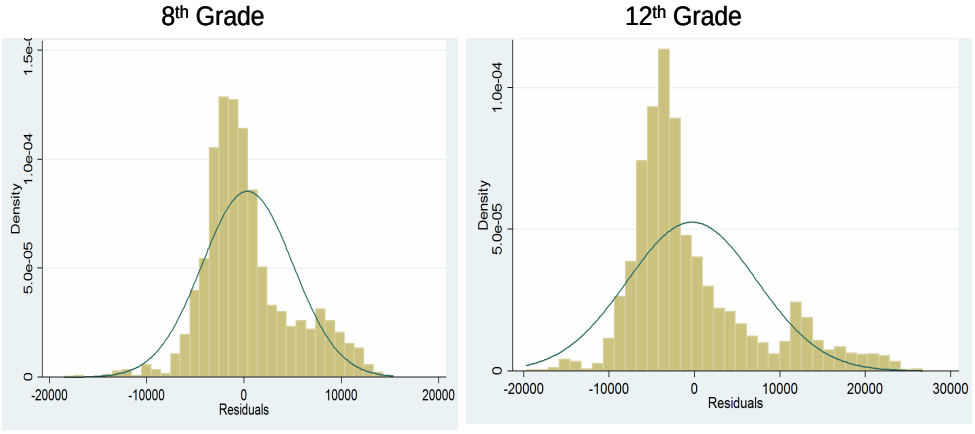

Figure 2: Distribution of savings conditional on family income, race, sex, past achievement.

The second case is more complex and requires the consideration of more variables. If parents of high ability students think their children will be able to get enough merit-based

financial aid to face all his/her postsecondary expenses, it might not be optimal to save and reduce current consumption. The child could afford the expenses anyway and parents could increase lifetime utility by increasing current consumption. The same logic could apply for need-based financial aid; i.e.., assigned based on family income. If this was the case we could observed a hump shaped relation between savings and ability breaking the monotonicity relation and so the identification strategy. But this argument is based on the assumption that the education decision depends only on the cost. However there could also be a quality dimension on that decision. Therefore, understanding how financial aid works and how it affects net price of attendance[11] at different postsecondary institutions is of vital importance to study whether the identification assumption is correct.

There are three sources of financial aid for students attending postsecondary institutions. The first, and most important in terms of budget, are financial need-based governmental sources (such as the Pell Grant, Perkin Loans, Sttaford subsidized loans and the Supplemental Educational Opportunity Grant (SEOG)). The second are governmental loans that are not need based, as the Stafford unsubsidized loans and the PLUS loans, but those are not commonly used in practice. Finally, colleges and universities offer their own grants which in most cases are merit based-in that they are assigned to students that attained a certain GPA in high school (usually above 3.0) or satisfy some other academic criteria.

An additional important aspect is that financial aid does not usually cover all postsecondary expenses. Parents should expect to pay at least half to two-thirds of their children's college costs through a combination of savings, current income, and loans. Gift aid from the government, colleges and universities, and private scholarships account for only about a third of total college costs. According to data from the Education Department for the 1995-96 academic year Lee (2001) finds that 91.9% of students attending postsecondary schools with tuition and fees above $12,000 receive some direct financial contribution from their parents. Among those students attending institutions with tuitions and fees below $12,000 this percentage was 79.6% in public research universities and 70.8% for other institutions. In sum, for most students the net price of attendance is positive.

Therefore the empirical evidence suggests that: financial aid is based on observables that we take care of in our estimation, and for most of the students it does not cover all of their

[11] Net price of attendance is usually defined as tuition plus room and board minus financial aid, i.e. what the student and/or family must cover after financial aid.

postsecondary education expenses. However, this argument does not rule out the existence of a hump shaped relation between ability and cost of postsecondary education. On one extreme of the distribution we could have students from economically disadvantage families getting financial aid and on the other extreme high ability students getting it. This could imply that only students from the center of the achievement distribution, who would not qualify for either need based or merit based financial aid, would face higher costs. However, this argument does not take into account other aspects that parents might take into account when choosing the postsecondary institutions for their children as for example the quality dimension of postsecondary education. If postsecondary costs are related to the quality of the institution and if the return to schooling depends on this quality, the previous argument does need not hold. To study the relation between a measure of students' ability and the cost of postsecondary education, I do a nonparametric regression between students' standardized composite SAT score and the actual net price of attendance they face for the students in the NELS88 sample. Figure 3 shows the result. The relation between SAT and net price of attendance is monotonically increasing, giving us evidence that there are some aspects other than price affecting the choice of the postsecondary institution. The next subsections explain in more detail each of the algorithm's steps.

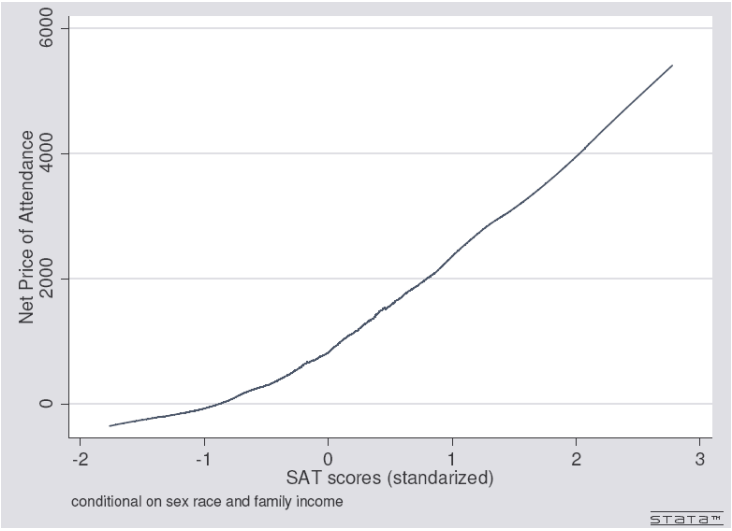

Figure 3: Net Price of Attendance and residual SAT

7 Appendix B: Tables

Table 1: Summary Statistics

Variable	8th Grade		12th Grade	
	Black	White	Black	White
Standardized math test score	0.300	0.520	0.290	0.530
	(0.245)	(0.284)	(0.249)	(0.284)
Home Inputs				
Hours reading outside school	1.748	2.032	2.147	2.585
	(1.719)	(1.912)	(2.118)	(2.497)
Hours of TV per week	3.499	2.673	3.209	2.085
	(1.651)	(1.514)	(1.694)	(1.447)
Special lessons	0.296	0.419	0.140	0.138
School Inputs				
Private school	0.142	0.225	0.069	0.155
Teacher wage	9.764	9.730	9.973	9.946
	(0.161)	(0.157)	(0.144)	(0.141)
Teacher experience	14.723	13.921	13.944	14.507
	(7.644)	(7.540)	(10.306)	(9.168)
Teacher certified	0.478	0.503	0.630	0.645
Class enrollment	26.596	24.476	27.083	27.058
	(13.096)	(11.005)	(14.935)	(17.026)
Prop. of stud receiving remedial classes	12.227	5.377	12.175	5.797
	(14.091)	(7.316)	(13.576)	(7.286)
Proportion of class maintaining order	2.100	1.990	1.815	1.591
	(0.853)	(0.785)	(1.019)	(0.761)
Family characteristics				
Mother High School	0.667	0.777	0.713	0.811
Mother Some College	0.346	0.429	0.370	0.441
Mother College	0.128	0.210	0.131	0.205
Father High School	0.357	0.642	0.367	0.672
Father Some College	0.205	0.422	0.216	0.442
Father College	0.112	0.263	0.104	0.261
Savings post secondary education	4,022	5,938	5,443	9,099
	(4,138)	(5,087)	(6,830)	(9,357)
Family Income	29,729	49,464	36,658	57,026
	(26,781)	(39,993)	(32,500)	(42,512)

Table 2: Distribution of fathers' education by mothers' education

		Mother's Education		
		High School	Some College	College
Father's	High School	37.1%	16.4%	6.6%
Education	Some College	16.6%	26.2%	10.9%
	College	12.0%	28.3%	66.2%

Table 3: Regression results grade-dependent technology

	OLS	O-P estimator
Lag test score	0.4951	0.6911
	(0.0142)	(0.0209)
Read in 8thG	0.0366	0.0375
	(0.0073)	(0.0074)
Read in 8thG squared	-0.0030	-0.0026
	(0.0011)	(0.0011)
Go to class with pencil 8thG	0.0244	0.0280
	(0.0110)	(0.0111)
Special lessons 8thG	0.0290	0.0275
	(0.0088)	(0.0089)
Family have books at home 8thG	0.0513	0.0465
	(0.0182)	(0.0183)
Hours of TV per week 8thG	-0.0169	-0.0154
	(0.0028)	(0.0028)
Time with parents 8thG	-0.019	-0.0269
	(0.0523)	(0.0536)
Log(teacher wage 8thG)	0.1038	0.0820
	(0.0282)	(0.0285)
Teacher experience 8thG	0.0011	0.0012
	(0.0006)	(0.0006)
1/(% students with single parents 8thG)	0.4297	0.4524
	(0.1596)	(0.1606)
Hours of classes 8thG	0.0668	0.0552
	(0.0356)	(0.0356)
1/(% students attending remedial classes 8thG)	0.0272	0.0209
	(0.0103)	(0.0104)
1/(prop class time teacher spends maintain. Order 8thG)	0.0970	0.0973
	(0.0188)	(0.0188)

Table 3 (contd.): Regression results grade-dependent technology

	OLS	PV estimator
Read in 12thG	0.0032	0.0031
	(0.0024)	(0.0024)
Go to class with pencil 12thG	0.0545	0.0563
	(0.0210)	(0.0212)
Family rule about hw 12thG	0.0353	0.0274
	(0.0135)	(0.0136)
Participate in community activities 12thG	0.0358	0.0304
	(0.0119)	(0.0121)
Go to the Theater 12thG	-0.0028	-0.0017
	(0.0178)	(0.0179)
Time with parents 12thG	0.0099	0.0014
	(0.0184)	(0.0185)
Log(teacher wage 12thG)	0.0776	0.0660
	(0.0396)	(0.0404)
Teacher has a master degree 12thG	0.0224	0.0146
	(0.0115)	(0.0112)
Teacher certified in math 12thG	0.0306	0.0221
	(0.0128)	(0.0129)
1/(% students attending remedial classes 12thG)	0.0079	0.0081
	(0.0135)	(0.0138)
1/(% students with single parents 12thG)	0.2334	0.2150
	(0.1009)	(0.1023)
1/(prop class time teacher spends maintain. Order 12thG)	0.0885	0.0663
	(0.0208)	(0.0213)

all specifications control for parents' education, race and sex

standard errors in parenthesis

Table 4: Regression results grade-dependent technology with cross effects

Lag test score	0.5515
	(0.0191)
Interaction Lag test score current inputs	1.5491
	(0.6628)
Read in 8thG	0.0233
	(0.0059)
Read in 8thG squared	-0.0020
	(0.0007)
Go to class with pencil 8thG	0.0182
	(0.0076)
Special lessons 8thG	0.0176
	(0.0063)
Family have books at home 8thG	0.0297
	(0.0125)
Hours of TV per week 8thG	-0.0097
	(0.0024)
Time with parents 8thG	-0.0869
	(0.0343)
Log(teacher wage 8thG)	0.0397
	(0.0186)
Teacher experience 8thG	0.0008
	(0.0004)
1/(% students with single parents 8thG)	0.2004
	(0.1055)
Hours of classes 8thG	0.0286
	(0.0223)
1/(% students attending remedial classes 8thG)	0.0127
	(0.0067)
1/(prop class time teacher spends maintain. Order 8thG)	0.0600
	(0.0153)

Table 4 (Contd.): Regression results grade-dependent technology with cross effects

Read in 12thG	0.0009
	(0.0012)
Go to class with pencil 12thG	0.0254
	(0.0123)
Family rule about hw 12thG	0.0103
	(0.0070)
Participate in community activities 12thG	0.0138
	(0.0069)
Go to the Theater 12thG	-0.0002
	(0.0091)
Time with parents 12thG	0.0018
	(0.0096)
Log(teacher wage 12thG)	0.0281
	(0.0211)
Private School 12thG	0.0071
	(0.0061)
Teacher certified in math 12thG	0.0128
	(0.0070)
1/(% students attending remedial classes 12 G)	0.0053
	(0.0070)
1/(% students with single parents 12thG)	0.0933
	(0.0549)
1/(prop class time teacher spends maintain. Order 12thG)	0.0265
	(0.0123)

Table 5: Accounting Exercise

Predicted gap		0.214
	gap closed by home inputs	0.034
		15.6%
	gap closed by school inputs	0.020
		9.2%
	gap closed by giving inputs only in 12th grade	
	home inputs	0.016
		7.4%
	school inputs	0.015
		7.2%
	gap closed by giving the same initial test score	0.035
		16.4%

Table 6: Robustness Analysis, accounting exercise

OLS predicted gap		0.235
	gap closed by home inputs	0.023
	gap closed by school inputs	0.079
PV current saving predicted gap		0.235
	gap closed by home inputs	0.021
	gap closed by school inputs	0.077
PV other period saving predicted gap		0.235
	gap closed by home inputs	0.020
	gap closed by school inputs	0.077
PV change in savings predicted gap		0.235
	gap closed by home inputs	0.020
	gap closed by school inputs	0.065

Table 7: Robustness Analysis, students that do not move. Accounting exercise

	Full Sample	Restricted sample
predicted gap	0.214	0.205
gap closed by family inputs	0.034	0.035
	15.6%	16.8%
gap closed by school inputs	0.020	0.022
	9.2%	10.6%

Table 8: Robustness Analysis, public school students. Accounting exercise

	Full Sample	Restricted sample
predicted gap	0.214	0.200
gap closed by family inputs	0.034	0.032
	15.6%	16.2%
gap closed by school inputs	0.020	0.015
	9.2%	7.6%

8 Appendix C: Derivation of the bias when savings are a poor proxy of ability to learn

From (13): $\eta_{it} = (1/\beta)(s_{it} - \zeta_{it})$, and plugging back in (12) we get:

$$\begin{aligned} h_{it} &= \gamma_0 + \gamma_1 I_{it} + \varepsilon_t + (1/\beta)(s_{it} - \zeta_{it}) \\ & \gamma_0 + \gamma_1 I_{it} + \frac{1}{\beta} s_{it} \underbrace{- \frac{1}{\beta}\zeta_{it} + \varepsilon_t}_{\mu_{it}} \end{aligned}$$

which implies that the unobserved component equals:

$$\mu_{it} = \varepsilon_{it} - \gamma_2 \zeta_{it} = h_{it} - (\gamma_0 + \gamma_1 I_{it} + \gamma_2 s_{it}) \tag{14}$$

where $\gamma_2 = 1/\beta$. This model can be rewritten in deviation of the means, which results:

$$\begin{aligned} \mu_{it} &= (h_{it} - \overline{h}) - \left[\gamma_1 (I_{it} - \overline{I}) + \gamma_2 (s_{it} - \overline{s})\right] \\ &= h_{it} - [\gamma_1 i_{it} + \gamma_2 s_{it}] \end{aligned}$$

which with some abuse of notation now lower case letters refer to deviation with respect to their mean. Thus the OLS estimates in this case can be derived from:

$$\min \sum \mu_{it}^2 = \min \sum \left[h_{it} - (\gamma_1 i_{it} + \gamma_2 s_{it})\right]^2$$

The FOC are:

$$\gamma_1 : \sum_i \left[h_{it} - (\widehat{\gamma}_1 i_{it} + \widehat{\gamma}_2 s_{it})\right] i_{it} = 0 \tag{15}$$

$$\gamma_2 : \sum_i \left[h_{it} - (\widehat{\gamma}_1 i_{it} + \widehat{\gamma}_2 s_{it})\right] s_{it} = 0 \tag{16}$$

In matrix notation:

$$x_t' h_t = x_t' x_t \widehat{\gamma} \tag{17}$$

where:

$$x_t' = \begin{pmatrix} i_{1t} & ... & i_{nt} \\ s_{1t} & ... & s_{nt} \end{pmatrix} = \begin{pmatrix} i_t \\ s_t \end{pmatrix}$$

and

$$h_t = \begin{pmatrix} h_{1,t} \\ ... \\ h_{n,t} \end{pmatrix}$$

From the FOC (17), we get:

$$\begin{aligned}
\widehat{\gamma} &= \left(x_t' x_t\right)^{-1} x_t' h_t \\
\widehat{\gamma} &= \left(x_t' x_t\right)^{-1} x_t' (x_t \gamma + \mu_t) \\
\widehat{\gamma} - \gamma &= \left(x_t' x_t\right)^{-1} x_t' \mu_t
\end{aligned}$$

Which implies that we can write the expected bias as:

$$E(\widehat{\gamma} - \gamma) = E\left[\left(x_t' x_t\right)^{-1} x_t' \mu_t\right]$$

$$E(\widehat{\gamma} - \gamma) = E\left[\begin{pmatrix} \frac{\sum s_{it}^2}{A} & \frac{-\sum i_{it} s_{it}}{A} \\ \frac{-\sum i_{it} s_{it}}{A} & \frac{\sum i_{it}^2}{A} \end{pmatrix} \begin{pmatrix} \sum i_{it} \mu_{it} \\ \sum s_{it} \mu_{it} \end{pmatrix}\right]$$

where $A = \left(\sum s_{it}^2\right)\left(\sum i_{it}^2\right) - \left(\sum i_{it} s_{it}\right)^2$. We can re write the expected bias more compactly as:

$$\begin{aligned}
E(\widehat{\gamma} - \gamma) &= E\left[\begin{pmatrix} \frac{s_t' s_t}{A} & \frac{-i_i' s_t}{A} \\ \frac{-i_i' s_t}{A} & \frac{i_t' i_t}{A} \end{pmatrix} \begin{pmatrix} i_t' \mu_t \\ s_t' \mu_t \end{pmatrix}\right] \\
E(\widehat{\gamma} - \gamma) &= E\left[\begin{pmatrix} \frac{s_t' s_t i_t' \mu_t - i_i' s_t s_t' \mu_t}{A} \\ \frac{-i_i' s_t i_t' \mu_t + i_t' i_t s_t' \mu}{A} \end{pmatrix}\right]
\end{aligned}$$

$$E(\widehat{\gamma} - \gamma) = \begin{pmatrix} \frac{\sigma_{i\mu}\sigma_{s_t s_t} - \sigma_{s_t \mu}\sigma_{i s_t}}{\left[\sigma_{ii}\sigma_{s_t s_t} - \sigma_{i s_t}^2\right]} \\ \frac{\sigma_{s\mu}\sigma_{i_t i_t} - \sigma_{i_t \mu}\sigma_{i s_t}}{\left[\sigma_{ii}\sigma_{s_t s_t} - \sigma_{i s_t}^2\right]} \end{pmatrix} \tag{18}$$

Note that the OLS bias when we omit the unobserved component η_{it} is:

$$E(\widehat{\gamma}_1^{OLS} - \gamma_1) = \frac{\sigma_{i\nu}}{\sigma_{ii}} = \frac{\sigma_{i\eta} + \sigma_{i\varepsilon}}{\sigma_{ii}} = \frac{\sigma_{i\eta}}{\sigma_{ii}}$$

Using the suggested proxy variable and assuming that all the components of the error term are orthogonal to current inputs; i.e.., $\sigma_{i\mu} = 0$, we can re write (18) as:

$$\gamma_1 : E(\widehat{\gamma}_1 - \gamma_1) = \frac{-\sigma_{s_t \mu}\sigma_{i s_t}}{\left[\sigma_{ii}\sigma_{s_t s_t} - \sigma_{i s_t}^2\right]}$$

$$\gamma_2 : E(\widehat{\gamma}_2 - \gamma_2) = \frac{\sigma_{s_t \mu}\sigma_{ii}}{\left[\sigma_{ii}\sigma_{s_t s_t} - \sigma_{i s_t}^2\right]}$$

In this particular example we can see that using savings as a proxy for ability provides estimates with a smaller bias than OLS, even when the relation between savings and ability is not determinist. To see this, consider the bias in $\widehat{\gamma}_1$:

$$\gamma_1 : E(\widehat{\gamma}_1 - \gamma_1) = \frac{-\sigma_{s_t \mu}\sigma_{i s_t}}{\left[\sigma_{ii}\sigma_{s_t s_t} - \sigma_{i s_t}^2\right]}$$

$$\gamma_1 : E(\widehat{\gamma}_1 - \gamma_1) = \frac{-\sigma_{s_t\mu}\frac{\sigma_{is_t}}{\sigma_{ii}}}{\left[\sigma_{s_ts_t} - \frac{\sigma^2_{is_t}}{\sigma_{ii}}\right]}$$

Consider first $\sigma_{s_t\mu}$:

$\sigma_{s_t\mu} = E\left[\sum\left(\beta\eta_{it} + \zeta_{it}\right)\mu\right] = E\left[\sum\left(\beta\eta_{it} + \zeta_{it}\right)\left(\varepsilon_{it} - \frac{1}{\beta}\zeta_{it}\right)\right]$

$\sigma_{s_t\mu} = E\left[\beta\sum\eta\varepsilon_{it} + \sum\zeta_{it}\varepsilon_{it} - \sum\eta_{it}\zeta_{it} - \frac{1}{\beta}\sum\zeta_{it}\zeta_{it}\right]$

$\sigma_{s_t\mu} = E\left[-\frac{1}{\beta}\sum\zeta^2_{it}\right] = -\frac{1}{\beta}\sigma^2_\zeta$

$\frac{\sigma_{is_t}}{\sigma_{ii}}$ can be expressed in terms of the bias of the OLS estimator when we do not use savings as a proxy for unobserved ability to learn. To see this more clearly:

$$\frac{\sigma_{is_t}}{\sigma_{ii}} = \frac{E\left[\sum i\left(\beta\eta_{it} + \zeta_{it}\right)\right]}{\sigma_{ii}} = \frac{E\left[\beta\sum i\eta_{it}\right]}{\sigma_{ii}}$$

since $E(\eta) = 0$, $E(\zeta) = 0$, and $\sum I\zeta_{it} = 0$ by assumption. Then

$$\frac{\sigma_{is_t}}{\sigma_{ii}} = \frac{\beta\sigma_{i\eta}}{\sigma_{ii}} = \beta E(\widehat{\gamma}_1^{OLS} - \gamma_1)$$

Replacing back in $E(\widehat{\gamma}_1 - \gamma_1)$:

$$\begin{aligned} E(\widehat{\gamma}_1 - \gamma_1) &= \frac{-\left(-\frac{1}{\beta}\sigma^2_\zeta\right)\frac{\beta\sigma_{i\eta}}{\sigma_{ii}}}{\left[\sigma_{s_ts_t} - \frac{\sigma^2_{is_t}}{\sigma_{ii}}\right]} = \frac{\sigma^2_\zeta\frac{\sigma_{i\eta}}{\sigma_{ii}}}{\left[\sigma_{s_ts_t} - \frac{\sigma^2_{is_t}}{\sigma_{ii}}\right]} = \frac{\sigma^2_\zeta E(\widehat{\gamma}_1^{OLS} - \gamma_1)}{\left[\sigma_{s_ts_t} - \frac{\sigma^2_{is_t}}{\sigma_{ii}}\right]} \\ &= \frac{\sigma^2_\zeta}{\left[\sigma_{s_ts_t} - \frac{\sigma^2_{is_t}}{\sigma_{ii}}\right]}E(\widehat{\gamma}_1^{OLS} - \gamma_1) \end{aligned}$$

To show that $E(\widehat{\gamma}_1 - \gamma_1) < E(\widehat{\gamma}_1^{OLS} - \gamma_1)$ wee need to show $\frac{\sigma^2_\zeta}{\left[\sigma_{s_ts_t} - \frac{\sigma^2_{Is_t}}{\sigma_{II}}\right]} < 1$, or $\sigma^2_\zeta < \left[\sigma_{s_ts_t} - \frac{\sigma^2_{Is_t}}{\sigma_{II}}\right]$. The first term of $\left[\sigma_{s_ts_t} - \frac{\sigma^2_{Is_t}}{\sigma_{II}}\right]$ can be rewritten as:

$$\begin{aligned} \sigma_{s_ts_t} &= E\left[\sum s^2_{it}\right] = E\left[\sum\left(\beta\eta_{it} + \zeta_{it}\right)^2\right] \\ &= E\left[\beta^2\sum\eta^2_{it} + 2\beta\sum\eta_{it}\zeta_{it} + \sum\zeta^2_{it}\right] \\ &= \beta^2\sigma^2_\eta + \sigma^2_\zeta \end{aligned}$$

where we use the fact that $E(\eta) = E(\zeta) = 0$. We can decompose the second term as:

$$\begin{aligned}
\sigma^2_{is_t} &= E\left[\sum i\left(\beta\eta_{it} + \zeta_{it}\right)\right]^2 \\
&= E\left[\sum i\zeta_{it} + \sum i\beta\eta_{it}\right]^2 \\
&= E\left[\sum i\beta\eta_{it}\right]^2 = \beta^2 E\left(\sum i\eta_{it}\right)^2
\end{aligned}$$

This implies:

$$\begin{aligned}
\sigma_{s_t s_t} - \frac{\sigma^2_{is_t}}{\sigma_{ii}} &= \beta^2\sigma^2_\eta + \sigma^2_\zeta - \beta^2\frac{E\left(\sum i\beta\eta_{it}\right)^2}{\sigma_{ii}} \\
&= \beta^2\left(\sigma^2_\eta - \frac{\sigma^2_{i\eta_{it}}}{\sigma_{ii}}\right) + \sigma^2_\zeta
\end{aligned}$$

therefore, we can write the expected bias as:

$$E(\widehat{\gamma}_1 - \gamma_1) = \frac{\sigma^2_\zeta}{\left[\beta^2\left(\sigma^2_\eta - \frac{\sigma^2_{i\eta_{it}}}{\sigma_{ii}}\right) + \sigma^2_\zeta\right]} E(\widehat{\gamma}_1^{OLS} - \gamma_1)$$

Then for $\sigma^2_\zeta < \left[\sigma_{s_t s_t} - \frac{\sigma^2_{is_t}}{\sigma_{ii}}\right]$ to hold, we need $\beta^2\left(\sigma^2_\eta - \frac{\sigma^2_{i\eta_{it}}}{\sigma_{ii}}\right) > 0$. Note that this last condition can be written in terms of the correlation coefficient between η and i:

$$\begin{aligned}
\beta^2\left(\sigma^2_\eta - \frac{\sigma^2_{i\eta_{it}}}{\sigma_{ii}}\right) &= \beta^2\sigma^2_\eta\left(1 - \frac{\sigma^2_{i\eta_{it}}}{\sigma^2_\eta\sigma_{ii}}\right) \\
&= \beta^2\sigma^2_\eta\left(1 - r^2_{i\eta_{it}}\right)
\end{aligned}$$

where $r^2_{i\eta_{it}}$ is the square of the correlation coefficient which is bounded by one. It follows that $\beta^2\left(\sigma^2_\eta - \frac{\sigma^2_{i\eta_{it}}}{\sigma_{ii}}\right) > 0$ will always hold. Therefore, the bias of the contribution of inputs on the production of achievement when we use savings as a proxy for ability to learn will never exceed the bias if we ignore that proxy.

9 Appendix D: More Characteristics of NELS:88

NELS:88 is a nationally representative sample of eighth-graders that were first surveyed in the spring of 1988. The original sample employed a two-stage sampling design, selecting first a sample of schools and then a sample of students within these schools. In the first stage the sampling procedure set the probabilities of selection proportional to the estimated enrollment of eighth grade students. In the second stage 26 students were selected from each of those schools, 24 randomly and the other two were selected among hispanic and Asian Islander students, resulting in approximately 25,000 students. A sample of these respondents (18,221) were then resurveyed through four follow-ups in 1990, 1992, 1994, and 12,144 were interview again in 2000. Along with the student survey, NELS:88 included surveys of parents, teachers, and school administrators. By beginning with the 8th-grade, NELS:88 was able to capture the population of early dropouts—those who left school prior to spring term of 10th grade—as well as later dropouts (who left after spring of 10th grade). The study was designed not only to follow a cohort of students over time but also to "freshen" the sample at each of the first two follow-ups, and thus to follow multiple grade-defined cohorts over time. Thus, 10th grade and 12th grade cohorts were included in NELS:88 in the first follow-up (1990) and the second follow-up (1992), respectively. In late 1992 and early1993, high school transcripts were collected for sample members, and, in the fall of 2000 and early 2001, postsecondary transcripts were collected, further increasing the analytic potential of the data.

Next the characteristics of each of the data collection years are summarize (See National Center for Education Statistics (2002) for a complete description):

Base-Year Study. The base-year survey for NELS:88 was carried out during the 1988 spring semester. The study employed a clustered, stratified national probability sample of 1,052 public and private 8th-grade schools. Almost 25,000 students across the United States participated in the base-year study. Questionnaires and cognitive tests were administered to each student in the NELS:88 base year. The student questionnaire covered school experiences, activities, attitudes, plans, selected background characteristics, and language proficiency. School principals completed a questionnaire about the school; two teachers of each student were asked to answer questions about the student, about themselves, and about their school; and one parent of each student was surveyed regarding family characteristics and student activities.

First Follow-up Study. Conducted in 1990, when most sample members were high school sophomores, the first follow-up included the same components as the base-year study, with the exception of the parent survey. The study frame included 19,363 in-school students, and 18,221 sample members responded. Importantly, the first follow-up study tracked base-year sample members who had dropped out of school, with 1,043 dropouts taking part in the study. Overall, the study included a total of 19,264 participating students and dropouts. In addition, 1,291 principals took part in the study, as did nearly 10,000 teachers.

Second Follow-up Study. The second follow-up took place early in 1992, when most sample members were in the second semester of their senior year. The study provided a culminating measurement of learning in the course of secondary school and also collected information that facilitated the investigation of the transition into the labor force and post-secondary education. The NELS:88 second follow-up resurveyed students who were identified as dropouts in 1990, and identified and surveyed additional students who had left school since the previous wave. For selected subsamples, data collection also included the sample member's parents, teachers, school administrators, and academic transcripts.

Third Follow-up Study (NELS:88/94). The NELS:88 third follow-up took place early in 1994. By this time in their educational careers, most of the sample members had already graduated from high school, and many had begun postsecondary education or entered the workforce. The study addressed issues of employment and postsecondary access and was designed to allow continuing trend comparisons with other NCES longitudinal studies. The sample for this follow up was created by dividing the second follow-up sample in 18 groups based on their response history, dropout status, eligibility status, school sector type, race, test score, socioeconomic status and freshened status. Each group was assigned an overall selection probability. Cases within a group were selected such that the overall probability was met, and the probability of selection within the group was proportional to each sample member second follow-up weight. The final sample size was 15,875 individuals.

Fourth Follow-up Study (NELS:88/2000). The fourth follow-up to NELS:88 (NELS:88/2000) included interviews with 12,144 members of the three NELS:88 sample cohorts 12 years after the base-year data collection (For costs reasons the third follow-up sample was subsample to limit the numbers of poor and difficult respondents and those who were unlikely to be located (those who couldn't be located during earlier follow-up interviews). From here 15,649

individuals were selected and 12,144 of them completed the survey). Because these data represent the period 6 years after the last contact with the sample, they will enable researchers to explore a new set of educational and social issues about the NELS:88 respondents. For example, in 2000, most of the participants from the various cohorts of NELS:88 had been out of high school for 8 years and were 26 years old. At this age, the majority of students who intend to enroll in postsecondary schools will already have done so. Thus, a large proportion of students have completed college; some completed graduate programs. Many of these young people are successful in the market place, while others have had less smooth transitions into the labor force.