The Returns to Education and Family Income*

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Abstract

Using a sub-sample of white males from the NLSY79, we show that individuals from poorer families exhibit higher marginal returns to education relative to their wealthier counterparts. This finding suggests that higher marginal costs, rather than inability to benefit from education, prevent these individuals from continuing their education. Our results are robust to OLS, IV and fixed-effects specifications that have been employed in the literature. We also show that the poor group is heterogeneous; it contains a group of individuals whose cognitive abilities are comparable to those of the most gifted rich, as well as a group of individuals who demonstrate non-cognitive problems and low cognitive abilities. These results suggest that policies aiming to increase educational attainment among the poor should differ depending on the target group.

1 Introduction

The observation that "the poor are where they are [because] they made the mistake of being born to the wrong parents", articulated by Michael Harrington (1962), was common knowledge for a long time before social scientists have documented substantial disparities in educational attainment across family income classes.

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The fact that children from high income families are much more likely to attend college than children from low income families do reflects either lower returns to education, lower 'ability to learn', or higher effective costs of schooling. However, the observed disparities are not sufficient to distinguish between these two competing explanations (benefits and costs). In educational settings, the evidence on imperfections in capital markets is mixed and inconclusive. Numerous studies have attacked this question almost exclusively through studies of the correlation between family income (or other family characteristics) and educational attainment. The positive correlation between family income and educational attainment has been widely interpreted as evidence supporting the idea that borrowing constraints hinder educational choices (see for example: Kane, 1994; Kane and Rouse, 1999; Ellwood and Kane, 2000; Rothstein and Rouse, 2007; Belley and Lochner, 2007; Brown, Scholz and Seshadri, 2007). However the step from correlation to causation is a precarious one as family income is also strongly correlated with family resources that foster cognitive and non-cognitive traits during child's formative years and her 'ability to learn' (including, Cameron and Heckman, 1998, 2001; Shea 2000; Keane and Wolpin, 2001, Carneiro and Heckman, and Cameron and Taber, 2004). Whether 'liquidity constraints' pose a barrier to lower-income people pursuing higher education is a topic of much debate. Separating between demand and supply factors is challenging especially since home environments affects both.

This paper takes a different route. Rather than estimating the effect of supply side factors on school choices we focus on the 'ability to learn' and the labor market returns to education. In theory individuals equate the marginal return to schooling with its marginal cost. If low income families face higher cost than families from higher income classes then their children, ceteris paribus, should invest less in schooling and exhibit higher marginal returns. Furthermore, if the gap in school attainments reflects solely disparities in the 'ability to learn' then children from different income classes should exhibit same returns to schooling at different margins. Motivated by Becker's theory of investment in human capital we identify the relevancy of supply side factors, by estimating the Mincerian returns to schooling across family income classes. Specifically, we focus on the following question: Do children from low income families exhibit higher marginal (wage) returns to schooling than their wealthier counterparts?

We are not the first to link home environments to children's 'ability to learn' (Carneiro, Heckman and Manoli, 2002) and to the wage returns to schooling (Altonji and Dunn, 1996). Yet, this paper is the first to utilize the Beckerian intuition to identify whether other factors other than monetary returns to schooling matter and assess the extent at which these explain the disparities in educational attainments across income classes. While the returns to schooling at the margin determine whether supply side factors overall matter, the returns to schooling cannot by themselves identify the underlying mechanism.

Family environments shape both the opportunities to borrow against future income - the 'liquidity constraint' channel - and other implicit costs (and benefits either monetary or in other markets) of schooling (for example psychic costs, benefits in marriage markets, network effect etc.). Separating between these channels is above the scope of this paper.

With this framework we turn to the data. Using data on white males from the NLSY79, we estimate the Mincerian returns to schooling by family income classes. School choices are not exogenous to potential benefits. This is a major concern in this paper as self-sorting to schooling on expected returns should vary with family income classes. Sorting is less likely to be random to returns the more expensive schooling is. In that case the sorting bias is negatively correlated with family income, which might lead us, mistakenly, to conclude that the returns to schooling of children from low income families are higher than the returns of their wealthier peers. To reduce potential biases in the estimated returns to schooling we utilize proxies for cognitive and non-cognitive traits formed by the mid teenage years, , commonly used instruments for schooling (Card, 1993; Angrist and Krueger, 1991) and between siblings variations in school attendance (Altonji and Dunn ,1996). Three main facts emerge: First, white children from low income families exhibit, on average and at the margin, higher Mincerian return to schooling than children from higher economic classes do,. Second, a substantial fraction of children born to low income families exhibit higher returns to schooling than their wealthier counterparts at the same level of schooling. Finally, we show that the poor group is heterogeneous; it contains a group of individuals whose cognitive abilities are comparable to those of the most gifted rich, as well as a group of individuals who demonstrate non-cognitive problems and low cognitive abilities.

This paper also relates to the literature on the causal impact of schooling on earnings. Over the last three decades, following Griliches' (1977) presidential address to the Econometric Society, a separate literature in economics aimed at estimating the returns to schooling purged of various biases. A large body of literature devoted to the estimation of 'causal' effects of schooling (see Card, 2001) has found that instrumental variables estimates of the return to schooling exceed OLS estimates. The argument this literature promotes is that instrumental variables estimates can be interpreted as estimating the return for those randomly assigned to schooling by the instrument; finding higher returns for changers suggests that they are credit constrained persons who face higher marginal costs of schooling; thus, generating a downward 'discount rate bias' in OLS estimates (Lang, 1993). Card (1993) and Lang (1993) argued that unequal access to sources of credit to finance school investments might help explain anomalously high instrumental variables estimates of returns to schooling. While the use of supply side factors to estimate rates of returns free of 'ability bias' and to identify, indirectly, evidence for liquidity constraints, is intuitive, the structural interpretation is driven, implicitly, from a particular model and relies on the assumption that instrument manipulates the 'constraint'. Therefore, Instrumental variables returns to schooling may exceed least squares estimates even if there are no 'short run' credit constraints (Carneiro and Heckman, 2002). In fact, using direct cost of schooling that need to be financed Cameron and Taber (2004) find no evidence for borrowing constraints. In contrast to these studies our approach indentifies the relevancy of supply side factors by estimating the returns to schooling, free of 'ability bias' and comparing the returns at the margin across family classes.

The paper unfolds as follows. Section 2 surveys the related literature on the importance of costs in educational decision and the literature on the estimation of the returns to schooling. Section 3 presents a model of endogenous schooling. Section 4 describes the data we used and our sample selection process. Section 5 discusses the results and Section 6 concludes.

2 Previous Work

The literature on the returns to education and the literature investigating the determinants of individuals' education choice (such as costs of education) mostly developed on separate paths. In this paper we adopt a unified approach and lean on both strands of the literature. We investigate the importance of differential costs on educational decisions, directly by estimating the returns to schooling and comparing them across family income groups. We now provide a review of both aspects of the literature.

2.1 Credit Constraints

There are plenty of empirical findings documenting that individuals coming from poor families have lower educational attainment. (Mare 1980; Manski and Wise 1983; Hauser

1993; Manski 1993; Kane 1994; Mayer 1997; Cameron and Heckman 2001; Levy and Duncan 2000). This correlation was shown in data from around the world in many stages of political and economic development (see a collection of studies in Shavit and Blossfeld (1993)). However, Carneiro and Heckman (2002) show that conditioning on family background characteristics and measures of ability the relation between family income and educational attainment weakens significantly.

Family income may be correlated with an individual's marginal cost of education but it has also been shown to be correlated with measures of cognitive and non-cognitive achievements that may affect schooling choices. Therefore, the interpretation of these correlations as evidence for credit constraints is not trivial.

The evidence on the importance of liquidity constraints in individuals' schooling decision is mixed. Kane, 1994; Elwood and Kane, 2000; Dynarski , 2001; Rothstein and Rouse, 2007; Belley and Lochner, 2007, Brown, Scholtz and Seshadri, 2007 all show that liquidity constraints play a major role in explaining educational achievements differentials. On the other hand Cameron and Heckman (1998, 2001), Shea (2000), Keane and Wolpin (2001), Carneiro Heckman and Manoli (2002) and Cameron and Taber (2004) do not find evidence for binding credit constraints.

Cameron and Heckman (1998, 2001) differentiate between short-term and long-term liquidity constraints. They argue that short term liquidity constraints apply to individuals who face higher discount rates than the going market rate. They do not find evidence for this type of credit constraints. These authors claim that limited access to funds during the early phases of a child's life, which they call long term liquidity constraints, lead to under investment in the development of skills required for success later in life, including in school. Since in their words "skill begets skill", when children coming from constrained families take the decisions on optimal level of schooling they rationally choose to invest less simply because their returns to the schooling investment is low.

2.2 The Returns to Education

Substantial research has been conducted to estimate the returns to schooling. Most of the attention was directed to the possibility of OLS estimators being upward biased due to the omission of ability measures that are correlated with education. However, OLS estimators can be downward biased as well. Griliches (1977) discusses the downward bias induced by measurement errors on the OLS estimator. Lang (1993) shows that if discount rates vary in the population and so is ability, then, even if the discount rate is not correlated with unobserved ability, OLS estimators will be downward biased because of "discount rate bias". This bias is caused since in equilibrium, conditional on schooling, individuals with a higher discount rate have higher levels of ability[1] . Carneiro, Heckman and Vytlacil (2001) argue that OLS estimators can be downward bias because of selection into education. Such a bias could occur, for example, if individuals who are at the top of the wage distribution working as college graduates will be at the bottom of the wage distribution had they worked as high-school graduates. They argue that the negative selection bias can offset and even reverse the sign of a positive sorting bias.

The likelihood of a bias in OLS estimation motivated researchers to look for instrumental variables (IV) methods. A comprehensive survey of this literature is provided by Card (2001). He shows that a bulk of research using supply side instruments finds IV estimates to be higher than the corresponding OLS estimates for the return to schooling. These findings stand in odds with the upward bias induced by unobserved ability[2]. Card (1993) and Lang (1993) interpret these results as evidence for liquidity constraints in education. Following Becker (1967) individuals optimally stop acquiring additional education when the marginal benefit from education equals its marginal cost. If marginal benefits and marginal costs vary in the population then in equilibrium individuals with higher marginal costs will have higher marginal benefits. The interpretation by Card (1993) of IV estimates in the presence of heterogeneous return relies on Imbens and Angrist (1994) who showed that in this case the IV identifies the average returns for individuals (LATE - Local Average Treatment Effect) affected by the instrument. Supply side instruments that, for example, lower the costs of schooling affect mainly the constrained population which is expected to have higher than average returns.

Altonji and Dunn (1996) estimate fixed-effects models controlling for family fixed-effects. Using data on brothers and sisters they control for interactions of parents education with own education. They get mixed results; some of the evidence points to a positive effect of mother education on the returns to schooling.

Cameron and Taber (2004) ask if liquidity constraints are an important determinant of schooling and they take a unified approach merging the knowledge from the literature on the determinants of schooling with the literature on the returns to schooling. They use IV methods together with structural models and conclude that there is no evidence

[1] Lang also shows that even if we could control for unobserved ability OLS might still be biased.

[2] This relation between IV estimates and OLS estimates was already demonstrated by Griliches(1977)

for short term liquidity constraints.

3 The Model

It is useful to discuss the econometrics problems and interpretation of the results in light of a model of endogenous schooling. We follow a model of individuals's educational choice introduced by Becker (1967) and Card (2001). The explicit model and notation is taken from Card although for brevity of exposition we do not show the model at full and just state the assumptions adopted by Card to get at these results.

Beginning at the age they leave school Individuals maximizes a discounted flow of utilities, over an infinite horizon, subject to their intertemporal budget constraint. Assuming that the marginal cost of the Sth year of schooling $(MC(S))$ rises faster than the marginal benefit from the Sth year of schooling $(MB(S))$ a necessary and sufficient condition for the optimal schooling decision is $MB(S) = MC(S)$.

Card specify the heterogenous marginal benefits from education and the marginal costs in the following form:

$$\begin{aligned} MB(S) &= b_i - k_1 S \\ MC(S) &= r_i + k_2 S \end{aligned} \tag{1}$$

where b_i is a random variable with a mean $\bar{b}$ and a variance σ_b^2. r_i is a random variable with a mean $\bar{r}$ and a variance σ_r^2.

From equation (1) and under a simplifying set of assumptions[3], the optimal schooling level is

$$S_i = (b_i - r_i)/k \tag{2}$$

where $k = k_1 + k_2$

The individual marginal benefit from schooling at the optimal schooling level derived from equation(2) is:

$$\beta_i \equiv b_i - k_1 S = b_i (1 - k_1/k) + r_i k_1/k \tag{3}$$

[3]Card uses the following assumptions: (i) log earning are additevely seperable in education and years of post-schooling experience;(ii) earnings are fixed over the lifecycle;(iii) earnigs while at school are equal to tuition costs;(iv) ignore disutility/utility form being in school;(v) instantaenous utility has the form $u(c(t)) = \log c(t)$;

There are two testable implications of the model, based on equations (2) and (3) ,which we use in the paper:

1. If individuals face the same marginal costs (called by Becker (1967) as "equality of opportunities") but the benefits from schooling vary in the population, then those acquiring more education have higher benefits from schooling (b_i) but the marginal benefit to schooling is equal to r for all individuals.

2. For the same level of schooling individuals with higher marginal benefits from schooling face higher marginal costs.

We will show that the marginal return to schooling is lower for individuals with higher levels of schooling, thus there is no "equality of opportunity". We will also show (Table 8) that comparing individuals with the same level of schooling, those coming from weaker socioeconomic status (and potentially have higher marginal costs) have higher returns to education.

3.1 OLS Estimation of the Return to Schooling

Equation (1)gives rise to the following relation between earnings and schooling:

$$\log y_i = \alpha_i + b_i S_i - \frac{1}{2} k_1 S_i^2 \tag{4}$$

Individual heterogeneity is expressed via the individual intercept (α_i) and the individual slope (b_i)

Defining $a_i \equiv \alpha_i - \alpha_0$ and replacing S_i with its optimal level from equation (2) equation (4)can be written as:

$$\log y_i = \alpha_0 + \bar{b} S_i - \frac{1}{2} k_1 S_i^2 + \left[\alpha_i + \left(b_i - \bar{b}\right) S_i\right] \tag{5}$$

Card shows that OLS estimation of equation (5)is subject to two potential biases. First, even in the absence of heterogenous returns $\left(b_i = \bar{b}\right)$ The standard ability bias exists since S_i may be correlated with α_i if individuals with higher ability face lower marginal costs. Second, in the presence of heterogenous returns, individuals with higher returns to schooling will tend to acquire higher levels of schooling thus generating a positive selection bias.

This way of writing the model of earning and schooling motivates a positive bias in OLS estimates. However OLS estimators can be biased downwards as well. Some of the reasons that were suggested for a negative bias are sorting (Carneiro,Heckman and Vytlacil,2001), "discount bias" (Lang, 1993), measurement errors (Grilliches,1977) and publication bias (Ashenfelter, 1999)

3.2 Instrumental Variables Estimation of the Return to Schooling

As shown by Card's model and well recognized by economists the OLS estimation of the causal effect of education on earnings using observational data yields biased estimators. One of the solutions suggested is the method of Instrumental variables. (IV). A recent approach in instrumental variables estimation is the use of supply side instruments.(e.g.: variation in the cost of education) to identify demand side parameters. Linear IV estimation of equation (5) may lead to an inconsistent estimator. Carneiro, Heckman and Vytalcil (1998) have shown that even if the instrumental variable is not correlated with α_i and $\left(b_i - \bar{b}\right)$ it may still be correlated with $\left(b_i - \bar{b}\right)$ conditional on schooling. Imbens and Angrist (1994) showed that if an instrumental variable (Z) is used to from an IV estimator for the returns to schooling than the probability limit of this estimator is:

$$\begin{aligned} & p\lim b_{iv} = cov\left[\log y_i, Z_i\right] \ / \ cov\left[S_i, Z_i\right] = \\ = \ & \frac{E\left[\log y_i \mid Z_i = 1\right] - E\left[\log y_i \mid Z_i = 0\right]}{E\left[\log S_i \mid Z_i = 1\right] - E\left[\log S_i \mid Z_i = 0\right]} = \frac{E\left[\beta_i \cdot \Delta S_i\right]}{E\left[\Delta S_i\right]} \end{aligned} \tag{6}$$

If β_i is independent of ΔS_i, which means individuals do not sort to education based on their high returns than $E\left[\beta_i \cdot \Delta S_i\right] = E\left[\beta_i\right] \cdot E\left[\Delta S_i\right]$ and the IV estimator is a consistent estimator for the average causal effect of schooling on earning since: $p\lim b_{iv} = E\left[\beta_i\right] = \bar{\beta}$. However, in the presence of heterogenous returns to education and if individuals sort into education based on their personal returns to equation (**??**) shows that the IV estimator is a weighted average of the personal returns to education where the personal return is weighted by the expression $\Delta S_i / E\left[\Delta S_i\right]$. This understanding of the way instrumental variable operate in the presence of heterogenous effects of education calls for a very careful interpretation of the estimates derived from IV estimation. One cannot interpret the estimate as the average treatment effect, that is the effect of the treatment (in our case one more year of schooling) on a random person chosen from the population but rather the local average treatment effect (LATE) on the population that is affected by the instrument.

3.3 The Statistical Model

We estimate the following statistical model and repeat the specification used by Card (1995):

$$Y_{it} = \alpha + \beta S_i + \gamma IND_{it} + \delta FAM_{it} + \theta_t + \varepsilon_{it}$$

Y_{it} is log of hourly wages of person i at time t. S_i is the highest numbers of school years completed (In Table 7 S_i is an indicator for college completion).IND_{it} is a host of individuals characteristics such as indicators for living in a smsa or in the south, region of residence and a quadratic in potential experience.

FAM_{it} includes indicators for parents' education and interaction between father's and mother's education, indicator for residing in smsa in 1979, indicators for region of residence in 1979, indicators for living with both parents at age 14 and an indicator for living with a single mother at age 14 θ_t are year fixed-effects and ε_{it} is an individual specific shock at year t

Throughout the paper we estimate the model by groups of family income per capita (quintiles or medians), parents' education (partitioned into five or two groups) or AFQT score (quintiles).

The partition into five groups of parents' education is done as following: (i) both parents have less than 12 years of schooling (ii) one parent has at least 12 years of schooling and the other parent has less than 12 years of schooling (iii) both parents have 12 years of schooling (iv) one parent has more than 12 years of schooling and the other parent has 12 years of schooling and (v) both parents have more than 12 years of schooling. The partition into two groups of parents' education is done a following: (i) both parents have less than 12 years of schooling, one parent has at least 12 years of schooling and the other parent has less than 12 years of schooling, both parents have 12 years of schooling and (ii) one parent has more than 12 years of schooling and the other parent has 12 years of schooling, both parents have more than 12 years of schooling.

4 The Data

We use the National Longitudinal Survey of Youth (NLSY) between the years 1979-2002. The NLSY can be divided into five main categories: (i) a cross-sectional sample comprised of 6,111 individuals; (ii) supplemental sample of Hispanics comprised of 1,480 individuals (iii) supplemental sample of Blacks comprised of 2,172 individuals

(iv) supplemental sample of economically disadvantaged Whites comprised of 1,643 individuals and (v) the military sample comprised of 1,280 individuals. We limit our sample to White males from the cross-sectional sample. This selection criteria was chosen for the following reasons: (i) we keep only white men in order to minimize estimation issues arising from labor-market participation, discrimination and fertility; (ii) We omit the economically disadvantaged supplementary sample because of doubts whether it is a representative sample (Macurdy,Mroz and Gritz (1998); Cameron and Taber (2004)), furthermore, this sample was discontinued after the interviews round of 1991 and (iii) the military sample is omitted because the majority of its individuals were not interviewed after 1983. This initial selection leaves us with 2,743 (43,901 interviewed observations between 1979-2002) individuals out of the 12,868 (205,703 observations interviewed between 1979-2002) in the NLSY. We want to restrict our measures of family income to the time before individuals begin post secondary education and most still live with their parents. Since family income is reported in the NLSY for the previous calendar year we restrict the sample to follow individuals who were 18 years old or younger in 1978. In our sample selection process we follow Card (1995) and keep individuals with non-missing reports about region of residence at age 14, family structure at age 14 (living with a single mother, living with both parents), smsa status in 1979, region of residence in 1979 and current region of residence. When parents' education was missing we imputed it to the sample mean (see Card(1993)). This selection process leaves 1403 individuals (17,646 interviewed observations)

For each individual we calculate an Index of Behavior based on self reported behavior questions provided by the BLS. The questions cover different aspects of behavior such as the use of alcohol and drugs, violent behavior, skipping school, interaction with the police or the juridicial system. The Index of Behavior was calculated in the following way: For each individual we generated an indicator receiving the value 1 if this individual responded "yes" to the question about his behavior and 0 otherwise (The index ignores the number of times each behavior was conducted in the previous year) We then summed all the indicators for each individual. For example, if a person's reported smoking marijuana 5 times in the past year, we added one to this person's index.

Throughout the paper we estimate regression models by family income at age 18. This measure was constructed using the following process: (i) we keep all individuals who have a non-missing report of family income in 1978[4] ,(ii). For individuals whose

[4]Most of our results are generated from estimating the parameters of interest by family income at

family income at age 18 is not available we impute family income. Our imputation process was as follows: (i) regress family income at age 18 on family income at age 15 and generate a predicted value of family income at age 18 based on family income at age 15 (ii) reiterate the process from (i) replacing, in every iteration, age 15 with ages 16-21 (iii) replace missing family income at age 18 with the predicted value generated by the closest age to 18.

4.1 Summary Statistics

The differences between individuals coming from families with different levels of incomes are not limited to years of schooling, thus it is plausible that both cost and benefits from education are associated with family income and a careful analysis should be employed to determine the causes for their relative lower educational attainment. Table 1 presents summary statistics of the differences, in several outcomes, between individuals by quintiles of income per capita at age 18. Panel A summarizes background variables. Individuals coming from richer families have better educated parents; more of them had lived with both parents at age 14 and did not reside with a single mother. Panel B describes educational attainment and cognitive achievements. Individuals coming from richer families have more years of schooling, higher fraction of high school graduates and college graduates. Their AFQT scores are higher as well. Panel D summarizes variables portraying behavioral self reports. There is some evidence of less problematic behavior (lower levels of the index) as family income increases. Most of the decline in the level of the index comes from fewer interactions with police or being accused in crimes. Measures like use of drugs and alcohol are pretty much similar across family income.

It is clear from Table 1 that lower levels of educational attainment of children from poor families can be attributed to various forms of higher costs either direct monetary costs or costs that are associated with inter-generational disutility from schooling or other non-cognitive problems. However, low family income is also associated with lower cognitive ability measures such as the AFQT scores hinting possibly to lower benefits from schooling as well.

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age 18 (divided into quintiles or medians). In the paper we will take effort to show that these results are robust to other measures of family income.

5 Results

5.1 The Mincerian Returns to Schooling

We begin our analysis using OLS estimation of the mincerian returns to education. Table 2 presents estimates for the mincerian return to school years completed by quintiles of family income per capita at age 18. There are two panels and five columns. The columns indicate the quintile of family income per capita measured at age 18. Panel A reports the coefficient on school years completed from a least-squares regression for a sample of individuals ages 25 and above. Panel B reports the coefficient on school years completed from a least-squares regression for a sample of individuals ages 30-38. In each panel we report results of three regressions. The first two rows report estimates controlling for individual characteristics then adding family characteristics. The third row reports estimates for a sub-sample of individuals who reported working full-time full-year. Two main findings emerge: (i) the estimated mincerian return to education is decreasing monotonically with family income (the exception is a slight stagnation between the third and the fourth quintile in panel A) (ii) in five out of six regressions the returns to education for individuals coming from the top of the family income (Q5) distribution is less than half (the difference is statistically significant) the mincerian return of individuals coming from families at the bottom of the family income distribution (Q1). The lowest Q1-Q5 difference estimate is 0.155-0.101 for individuals ages 25 and above controlling only for individual characteristics. The largest Q1-Q5 estimated difference is 0.204-0.041 for individuals working full-time full-year who were at most 38 years old, controlling for individual and family characteristics[5].

OLS estimators for the return to schooling may be subject to various upwards and downwards biases and do not provide consistent estimates for any well defined parameter (or treatment effect). As such the evidence provided in Table 2 does not show that the marginal (or even average) returns to schooling decreases with family income. It certainly may be the case that the pattern presented in Table 2 is due to the OLS estimates being downward biased for those coming from richer families (a dominant negative selection bias) while the estimates for those coming from low income families are biased upwards (dominant positive sorting gains)[6]. Nevertheless, the declining

[5]See Table W1 for the same specifications as in Table 2 estimated by family income at age 18 rather than family income per capita at age 18. The declining pattern of return is kept but is less steep suggesting that the amount of resources per child is an important factor.

[6]If the bias in the OLS estimation goes in the same direction for all income quintiles then our estimates for the differences in the OLS estimates are less biased then each individual estimate. Infact, as we show later, we do not find evidence for differences in the sign of the bias by quintiles of

pattern of the mincerian return to schooling has not been shown in the literature so far. This finding is robust to age and labor force participation. Moreover, the relatively large gaps in the estimated mincerian returns by family income provide a first glance at the large magnitude and unique pattern of bias that is needed to reverse the result. It is worth noticing that under the assumption of a quadratic relation between earnings and schooling a sufficient condition for showing that marginal returns are higher for one group relative to another is that the average return for this group is higher (for proof see web appendix). The estimates we present in Table 2 are probably biased estimates for the average treatment effect of schooling on earnings, however, if the order of the average returns after correcting for the bias remains unchanged than these estimates suggest that individuals coming from families with lower income have higher marginal returns. If the earnings-schooling relation is quadratic the results presented in Table 2 could arise just because children to low income families obtain lower level of schooling while being on a lower demand curve. We show that the declining pattern of returns to schooling is true at any school level margin. Figure 2 presents estimates of the mincerian returns to schooling from a quadratic specification of the relation between earnings and schooling (in Figure 2b we controll for AFQT and Index of Behavior). For each quintile of family income we calculated the projected marginal return at 8,10,12,16 and 22 years of schooling. The figure shows that the projected marginal (mincerian) return for any of these schooling levels is higher the lower family income per capita is. There are very large differences between the bottom and the top quintiles. On average the mincerian return of individuals at the top quintile is about 25% the return of individuals coming from the bottom quintile and the result is robust to adding controls for cognitive skills (AFQT) and non-cognitive behavior (Index of Behavior). The results presented in Table 2 and Figure 2 might be interpreted as if return to schooling is declining with the monetary cost of schooling if low income families faced higher costs of schooling. This is not what we claim. We do not provide evidence that the marginal monetary cost of education is higher for individuals with low parental income. It may be the case that the evidence of higher returns associated with lower levels of schooling can be attributed to other differential costs, such as disutility from school among individuals with low parental education

Carneiro and Heckman(2002) provide an argument against the importance of credit constrains in explaining variations in educational attainment. This argument is based on (i) the evidence of higher returns to education for high ability individuals and the

family income

fact the high ability is positively correlated with family income and (ii) some evidence in Altonji and Dunn (1996) for higher returns to schooling for individuals coming from more educated families. In Table 3 we estimate the mincerian return to schooling by five groups of parents' education and five quintiles of age adjusted AFQT. The results we present in this sample and our specification[7] is different than the results by Carneiro and Heckman(2002) and Altonji and Dunn (1996).

5.1.1 The Mincerian Return to Schooling by Parents' Education and AFQT

Table 3 presents a comparison of estimates of the mincerian return to school years completed by quintiles of family income with estimates by five groups of parents' education and five quintiles of AFQT

There are three panels and five columns. In panel A, the columns indicate the quintile of family income per capita at age 18, In panel B, the five columns indicate parents' education group and in Panel C, quintiles of AFQT. The results in the first row of each panel are the mincerian return to school years completed controlling only for individual characteristics. The results in the second row of each panel are the mincerian return controlling both for individual and family characteristics. In Panel A each regression is estimated separately by quintiles of family income. In Panel B each regression is estimated separately by five groups of parents' education. In Panel C each regression is estimated separately by quintiles of AFQT. Two main findings emerge: (i) The pattern of the estimates for the mincerian return (See Table 2) repeats itself when the sample is partitioned into five groups of parents' education. The coefficient from the OLS regression is declining with parents' education and the return to education in the fifth (high education) group is about 50% the estimated return for the first (low education) group (ii) There is no clear pattern for the mincerian return when estimated by quintiles of AFQT.

The evidence presented in Table 3 suggests that in our NLSY sample there is no strong evidence to support the claims that returns to schooling rise with parents' education or ability (proxied by AFQT). First, we find that the mincerian returns are lower for individuals coming from more educated families .Second, we show that while individuals from more educated or richer families have higher levels of ability (measured by AFQT scores; see Table 1) the mincerian return to schooling can be negatively correlated with family income and have no correlation (or possible slight positive correlation) with measures of ability. This finding is not in contrast with the

[7] We follow the model specification used by Card (1995)

declining returns by family income. If indeed there are high ability individuals who study less than is optimal (possibly due to higher cost), than it may be the case that returns increase with AFQT and at the same time decrease with parental income or education..

Table 3 supports the hypothesis that there are individuals coming from weaker background who possess high return to schooling and have lower levels of education, but cannot provide evidence that the costs preventing individuals with higher returns to take additional schooling are short terms financial costs, pshycic costs or differential prefernces towards school. However, we do not find strong evidence that long term financial constraints represented by lower cognitive test scores are the main factor for the significant lower returns to schooling for individuals coming from poor families.

5.1.2 Omitted Variables Bias: Mincerian Return Controlling for 'Unobservables' Cognitive and Non-Cognitive Measures

The concerns about the interpretation of the findings presented in Table 2 and Table 3 call for a more convincing analysis to recover the patterns of the marginal returns to schooling by family income. We aim to show that the declining pattern of the returns to schooling is robust to most estimation procedures employed by the literature on the returns to education. We continue with OLS estimation controlling for omitted cognitive and non-cognitive skills, by family income per capita.

OLS estimators are prone to various sources of upward and downward biases. We compare OLS estimators between groups that might be very different from each other and therefore be subject to differential biases. In particular it is plausible to expect higher positive sorting bias for individuals coming from low income families. This raises the concern that if the differential bias is corrected the decreasing pattern reported so far will not sustain. The NLSY provides measures of cognitive and non-cognitive characteristics that may serve as proxies for traits individuals sort on but are usually not observed by the econometrician. Table 4 presents estimates for the relationship between school years completed, AFQT Scores and Non-Cognitive Behavior. The table indicates that these measures have a significant effect on the levels of schooling attained by individuals and therefore suggests that OLS estimation omitting such measures generates biased estimates.

There are three panels and two groups of five columns. In the first group of five columns each regression is estimated separately by five quintiles of family income at age 18 without controls. In the second five columns group each regression is estimated separately by five quintiles of family income per capita at age 18 controlling for family and background variables. The dependent variable in all panels is the number of school years completed. Panel A reports the coefficient on AFQT, panel B reports the coefficient on the index of Non-Cognitive behavior and panel C reports the coefficient on AFQT scores and index of Non-Cognitive behavior from a regression that includes both. Three main findings emerge: (i) the coefficient on AFQT is positive and increases from the lowest quintile to the top quintile of family income when controls of background characteristics are not included. This result also holds after including the index of non-cognitive behavior (see Panel C). The Q1-Q5 difference is 0.046-0.069 and is statistically significant (ii)) the coefficient on the non-cognitive Index of Behavior is negative but does not show a clear pattern across quintiles of family income (iii) After controlling for background characteristics, inter-quintiles differences in the coefficient on AFQT are negligible and do not show a clear pattern across quintiles of family income. This result holds also in panel C once index of Non-Cognitive behavior is introduced into the regression (iv) Controlling for background characteristics, inter-quintiles differences in the Index of Behavior do not exhibit any clear pattern and are not statistically significant.

The table makes clear that both cognitive and non-cognitive variables are important determinants of educational attainment. However, only AFQT test scores exhibit a clear differential pattern among family income per capita groups. This pattern is consistent with the conjecture of stronger selection on ability among poor individuals After controlling for parents' education, age and family structure at the time an individual was growing up this pattern disappears. These results suggest that the differential selection into school on cognitive and non-cognitive characteristics by family income may not be a severe problem in this data.

The results presented in Table 4 make clear that cognitive and non-cognitive characteristics of individuals have an important effect on schooling outcomes. Even if these traits do not have a significant differential effect between income groups in schooling outcomes, they can have a differential effect in the labor market. Table 5 presents estimates for the mincerian return to school years completed by quintiles of family income per capita controlling for cognitive and non-cognitive measures

There are three panels and two groups of five columns. In the first group of five columns the mincerian return to schooling is estimated separately by five quintiles of family income at age 18 without controls. In the second five columns group each regression is estimated separately by five quintiles of family income at age 18 controlling for family and background variables. Panel A reports the coefficient on years of schooling completed and AFQT, panel B reports the coefficient on years of schooling completed and on the index of Non-Cognitive behavior and panel C reports the coefficient on school years completed, AFQT scores and Index of Behavior from a regression that includes both. Four main findings emerge and they hold when we control only for individual characteristics and also after introducing family background characteristics: (i) The mincerian return to education is decreasing monotonically with family income at age 18[8] (ii) the return to education in the fifth family income quintile is at least half the return in the first quintile. This difference is statistically significant when controlling for individual and family characteristics (iii) the coefficient on AFQT is positive and statistically significant but it does not show a clear pattern across quintiles of family income per capita. (iv) the coefficient on the Index of Behavior does not show a clear pattern, either in sign or magnitude, across quintiles of family income. It is insignificant in all specifications.

The pattern of a monotonic decline in the mincerian return to schooling remains after accounting for selection on variables that are usually not observed to the econometrician. If our measures of cognitive and non-cognitive traits account for a significant portion of those differences among individuals coming from different economic backgrounds then the findings of Table 2 cannot be attributed mainly to differential selection on unobservables (in Figure 2b we repeat the quadratic specification of Figure 2 controlling for AFQT and Index of Behavior. The declining pattern of the marginal returns is kept intact). The combined results of Table 4 and Table 5 are encouraging since they provide some evidence that the effect of omitted variables might not be very different between income groups. Thus, although OLS estimates might still be biased, these results give hope that the pattern of the bias does not reverse the declining patterns of the returns. With this understanding in mind we turn to methods of fixed-effects and instrumental variables estimation.

5.2 Fixed-Effects Estimation of the Returns to Schooling

Altonji and Dunn (1996) estimated the effect of parents' education on the returns to schooling of their children. Employing samples of men and women (separately) from the NLS and PSID,. they estimated OLS and fixed effects models allowing for interactions of years of schooling completed with both father and mother education. They obtained mixed evidence on whether parental education raises the return to education. In their

[8] However, the level of all estimates falls by about 25%

preferred specification for men, in the NLS, they find positive and insignificant effect for father education and positive significant effects for mother education. The results for men in the PSID show negative effects for father education and positive effects for mother's education. The estimates for women in the NLS show again a negative effect for father education and positive for mother education. The results for women in the PSID are negative effects of both father and mother.

Tables 6 estimates the effect of parents' education on the returns to school years completed following the preferred specification used by Altonji and Dunn in the NLS data. We then repeat the estimation while changing the specification of parents' education to the partition we employ in this current paper.

There are two panels and four columns. Panel A reports the returns to school years completed allowing for interaction of school years completed with parents' education and AFQT scores. This specification was used in Altonji and Dunn (1996). Panel B estimates the specifications of panel A, however, using an indicator for parents having high (or low) education. Two main findings emerge: (i) In panel A the coefficients on the interaction of mother's education with school years completed are negative and statistically insignificant. The interaction of father's education with school years is positive and statistically significant. (ii) In panel B the coefficient on the interaction of parents' education with education is statistically significant and negative.

Altonji and Dunn's specification of parent's education in the wage regression is conceptually different than our specification. rather than allowing a seperate interaction of father and mother's education with the child's education we introduce an interaction of the child's education with an indicator variable for parents with high education (see our division in section (3.3)). This sepcification follows our thinking that parents' education effect on the child's return to education is not seperable.

Some of the differences between our resulrs and Altonji and Dunn (1996) could possibly be explained by the marriage patterns in our data. Among poor families wives are more educated than their husband while this pattern is reversed among the richer group. Thus, the effect of higher mother education given father's education is to increase the estimated returns. we now turn to estimation of the marginal return to education using IV methods.

5.3 Instrumental Variables (IV) Estimation of the Returns to Education

The evidence shown so far using OLS estimation is suggestive and is not strong enough to establish the claim that the marginal return to education of the poor is greater than that of the rich. Even if our OLS estimators were consistent estimators for the average treatment effect, this would not prove, without additional assumptions, that marginal returns to schooling are higher for individuals coming from lower socioeconomic background, measured by family income or parental education. Ideally, we would like to compare the marginal return of individuals by family income and show that the returns are higher for those coming from poorer families. Such an exerscise will prove that poorer individuals face higher marginal cost to education, be it monetary or other type of costs. We now employ instrumental variables estimation to identify the marginal returns to schooling by family income. We use two of the instruments suggested by the returns to education literature: proximity to college (Card 1993) and quarter of birth (Angrist and Krueger (1991)). There are four potential problems, noted by the IV literature, associated with the use of these instruments and the interpretation of the results: (i) both instruments were criticized for being invalid instruments which do not satisfy the exclusion restriction[9] (ii) even if these IV variables were valid, they may be 'weak instruments' especially, when applied to sub-samples of the data and (iii) in the presence of heterogeneous effects the instruments identify the local average treatment effect (LATE) for individuals complying with the treatment administered by the instrument. The complying individuals may not be comparable between groups of family income, thus we end up comparing apples to oranges and (iv) since individuals with richer parents have higher educational attainment relative to their poor counterparts, IV will recover LATE at different margins of schooling and the estimates generated will be mechanically higher for individuals with lower levels of schooling.

We do not deal with the first issue and use the instruments that were suggested in the literature without any modification. Indeed if the instruments are not valid instruments one cannot learn much by using them, however, the contribution of this paper is not in suggesting new IVs. The issue of interpreting results stemming from weak instruments is not a simple one. We will follow the methods suggested by Angrist and Pischke (2009: 212). We will not be able to deal with the last two complications of IV mentioned above due to small sample size. While the estimates provided by the IV estimation is subject to criticism we find it necessary to show that such an estimation, given the caveats, at least maintains the pattern of declining returns to education with family income per capita and does not reverse our results.

[9]Some of the qritique about the use and interpretation of both instruments can be found in Bound, Jaeger and Baker (1995); Carneiro, Heckman and Vytlacil (2001); Carneiro and Heckman (2004); But also see Cruz and Moreira (2005) who argue for a very small bias in Angrist and Krueger (1991) specification of state of birth interacted with quarter of birth.

IV estimates tend to have higher standard errors and therefore we try to have a larger sample for the IV analysis. The way to do it is to perform the estimation by groups of parents education which is reported for everyone in the sample. The main issue with this partition of the sample is the interpretation of the results. Indeed parental education and family income are highly correlated however they are not the same. We take a careful approach. So far, even when estimating the returns by family income we did not claim that this is evidence for the existence of financial constraints. Our claim is that the fact that we observe individuals that come from weaker socioeconomic background obtain lower levels of schooling cannot be attributed only to costs since at least some of these individuals have high returns. This type of interpretation of the pattern declining returns to education is still maintained. In Table 3 we showed that returns to education decline also with parents" education and so the partitioning of the data we suggest seems to be consistent with previous estimation. In the division of the sample we use the specification described in section (3.3).[10]

5.3.1 IV Estimation: Proximity to College

Card (1993) used and indicator for the presence of college in the labor market where an individual resided at age 14. He finds, in the Young Men NLS, that individuals who grew up in a locality with a presence of a 4-year college have significantly higher levels of education and earnings. This differential persisted after controlling for regional and family background factors (including parental education and family structure). The effects of a nearby college were largest for men with the lowest predicted levels of schooling attainment, suggesting that the presence of a local college lowers the costs and/or raises the perceived benefits of education among children coming from weaker

[10]Estimation of the mincerain return by partitioning the data into two group is presented in Table W2. This table shows estimates for the minicerian return to school years completed by medians of family income per capita controlling for cognitive and non-cognitive measures. The table presents estimates for the minicerian returns to education by medians of family income per capita at age 18. Two main findings emerge: (i) the mincerian return to education of the top median of family income is between 35-50% less than the return to education of the bottom median of family income per capita. All differences are statistically significant. (ii) controlling for AFQT reduces the magnitude of the mincerian return to education but the inter-median difference remains large and statistically significant (iii) the coefficient on AFQT is about 10% higher (3.8 percentage points) for the top median of family income and the difference is insignificant (iv) controlling for AFQT, the index of Non-cognitive behavior has no significant effect on wages, neither economically nor statistically. Figure W1 shows the projected mincerian returns for different levels of schooling from a quadratic specifiaction estimated by medians of family income. It make clear that for every level of schooling the marginal mincerian return is higher for individuals coming from the bottom median of the family income

backgrounds.

Tables 7 presents OLS and IV estimates for the return to school years completed by two groups of parents' education using proximity to college as the instrumental variable. There are two panels and six columns. Panel A reports the coefficient on school years completed controlling for individual and family and background variables. Panel B reports the coefficient on an indicator for college completion[11] controlling for individual, family and background variables. The results in the first two columns are from a least-square regression by two groups of parents' education. The next four columns report IV results using Proximity to College as the instrument (2SLS : columns 3-4 and LIML: columns 5-6) by two groups of parents' education. Two main findings emerge: (i) both least-squares and IV estimates are higher for the group with lower parents' education. This holds for the returns to school years as well as the returns to college completion (ii) estimates for the returns to college (Panel B) for the group with higher parents' education remains fairly stable when estimated by least-squares or IV (iii) F-statistic for the first stage is low (around 3) for the return to schooling (iv) F-statistic for the first stage in the returns to college is 4 for the low group and 13 for the high group. (v) LIML estimates are not very different than the 2SLS estimates (vi) Hansen J Statistic P-value for college graduates coming from families with high parental education is 0.072.

The results presented in Table *7* provide additional support for the evidence presented so far. Using the larger sample and partitioning of the data into two groups by parents' education does not change the OLS results. Under the assumption that the instrument is valid and that the treatment assigned by the instrument is to lower marginal costs for both groups, IV results suggest that the marginal benefit to schooling is higher for individuals coming from lower backgrounds. The IV results in Panel A might be less convincing since the instrument is weak for both groups but the LIML estimates are not very far from the IV estimates. The IV result presented in Panel B show that the marginal return to college for individuals with weaker background is much higher than that for their counterparts. LIML and 2SLS estimates are very close to each other 0.77 and 0.86 respectively for the low education group and 0.25 and 0.24 for the high education group. The first stage for the higher education group is strong and the OLS, 2SLSL and LIML estimates very similar in magnitude (0.26,0.24 and 0.24 respectively). This provides some direct evidence that the fact the IV estimates are higher than OLS estimates comes from the high returns to individuals coming from

[11] Card (1995) does not estimate the return to college completion which we show in Panel B

weaker background. We do not find evidence for $IV > OLS$ for individuals with more educated parents.

5.3.2 IV Estimation: Quarter of Birth

Another supply side instrument was used by Angrist and Krueger (1991) to estimate the return to schooling in the Census data. These authors observed that most states in the US require students to enter school in the calendar year at which they turn six. This institutional constraint generates variations in school start age where those born later in the year will enter school when they are younger than 6. Since compulsory schooling laws require students to remain in school until their 16th birthday, then individuals who were born later in the year will reach the drop out age later in the year or at higher grades thus generating variation in the level of schooling based on the quarter of birth of the student.

Tables *8* presents OLS and IV estimates for the return to school years completed by two groups of parents' education using quarter of birth interacted with state of residence at age 14 Quarter of birth in our sample is a very weak instrument and is not even statistically siginificant in the first stage for the group with high parental education[12]. Nonetheless, since the use of Quarter of Birth is a milestone in the estimation of the returns to education we apply it to our sample We cannot claim that using quarter of birth as an instrument provide consistent estimates for the marginal return to education, however they do not reverse the results found so far.

There are two panels and six columns. Panel A reports the coefficient on school years completed controlling for individual, family and background variables. Panel B reports the coefficient on an indicator for college completion controlling for individual, family and background variables. The results in the first two columns are from a least-square regression by two groups of parents' education. The next four columns report IV results using Quarter of Birth interacted with state as the instrument (2SLS and LIML) by two groups of parents' education. Two main findings emerge: (i) both least-squares and IV estimates are higher for the group with lower parents' education. This holds for the returns to school years as but the estimates for the returns to college completion appear to be meaningless (very low or negative) (ii) estimates for the returns to school years (Panel A) for both groups of parents' education remain

[12]This may not be surprising. It is plausible that the group of individuals that are influenced by the instrument come from weaker families while most of the individuals who have a stronger family background do not dropout at 16.

fairly stable when estimated by least-squares or IV.(ii) F statistic for the first stage is marginally significant for individuals from low parental education and lower then 1 for their counterparts having more educated parents.

5.4 Local Average Treatment Effect: Estimating the Returns to Education for 'poor and rich' at the Same Schooling Margin

A large body of research emphasized the importance of the environment a child grows in. Parents education and income at young ages have been demonstrated to provide the basis for the acquisition of skills at later stages of life. The evidence presented so far may seem to be at odds with this results hinting that children of the poor are a homogenous group having high returns to education and could gain more education if only the constraints were alleviated. In this section we are trying to reconcile the findings of this paper with this vein of the literature. We show that children of poor families comprise a heterogeneous group that consists of highly skilled individuals as well as individuals with low cognitive levels and exhibit high levels non-cognitive problems. The findings presented in this section suggest that policies targeted towars increasing educational attainment among the poor should be differential depending on the group being targeted.

Tables 9 presents OLS estimates for the return to school years completed and college completion by two groups of parents education and two medians of AFQT. There are three panels and four columns. Panel A reports summary statistics for each of the four groups. Panel B reports the returns to school years completed. Panel C reports the coefficient on a dummy for completing college The first two columns report results from regressions models estimated separately for individuals whose parents are defined to have low education. These columns are further divided into two columns by medians of AFQT scores. The last two columns report results from regressions models estimated separately for individuals whose parents are defined to have high education. These columns are further divided into two columns by medians of AFQT scores. Two main findings emerge: (i) the two middle groups (individuals with high AFQT scores and those with low parents education; individuals with low AFQT scores and high parents education) are similar in their levels of education however those with high AFQT scores and low parents' education have higher AFQT scores and higher returns to schooling. (ii) the estimated returns to college for the individuals with low AFQT scores among the low parents' education group is the lowest of all groups.

The comparison made in the two middle columns suggests that there is a group of individuals among those coming from weaker background that has higher returns to schooling relative to their counterparts coming from better background and have the same level of schooling. One testable implication of the model we employ in this paper is that if two individuals have the same level of education, the one with higher marginal benefit should have higher marginal costs. We are not claiming to identify the source of these costs. Any cost that is associated with low parent's education might be the cause.. It is encouraging that the AFQT scores of the group with higher returns is higher so at least other measures of ability that are considered to be positively correlated with the benefits from schooling are higher for this group. The table also shows that this group has a lower score on the Index of Behavior suggesting that the higher costs these persons face are not non-cognitive costs captured by this specific index. The low AFQT group among those with lower background has about two years less of schooling but have somewhat lower returns to education and significantly lower returns to college than their high ability counterparts. This suggests that part of the reasons these individuals have lower educational attainment is due to lower benefits from schooling (possibly also higher costs that are associated with their high score on the non-cognitive index). The latter finding is in accord with the vein of the literature claiming that long terms financial constraints are the source for lower ability to benefit from schooling. The first finding suggests that there is a group among those coming from weaker background that could benefit from schooling but face high marginal costs. Finally, the group of individuals with the highest level of parents' education, own education and AFQT scores have low marginal returns suggesting they face low marginal costs. One policy implication that is suggested by these results is that first order treatment for the low AFQT group among the poor should be early intervention while for the high AFQT group the first order policy should be better access to credit.

6 Conclusion

This paper shows that individuals who have low-income families or less-educated parents have higher marginal returns to schooling than do individuals from richer, more-educated families. It is well documented that the poor stop schooling earlier and have fewer educational attainments than the rich. If individuals optimally stop school when their marginal benefit from additional education equals to the marginal cost, then our results suggest that individuals from low-income families have lower levels of educational attainment because they face higher costs of schooling, not because they cannot gain from further education. In the absence of family credit data, we cannot pinpoint the source of these costs, and the issue should be further investigated. Our approach is to estimate the returns to schooling by employing most of the common methods that were suggested by the. The results show a monotonic decrease in the returns to schooling with family income. We begin by estimating the returns to schooling using OLS, controlling for measures of cognitive and non-cognitive traits. Next, we employ a fixed-effects (within families) estimator used by Altonji and Dunn (1996). Finally, we employ instrumental variables estimation using an indicator for proximity to college (used by Card (1993)) and quarter of birth (used by Angrist and Krueger (1991)) as instruments. We also show that the poor group is heterogeneous; it contains a group of individuals whose cognitive abilities are comparable to those of the most gifted rich, as well as a group of individuals who demonstrate non-cognitive problems and low cognitive abilities. While policies that lower the cost of education may help to increase the educational attainment of the former group, improving educational attainment among members of the latter group may require policies that increase ability to benefit from education. It has been noted in the literature that IV estimates of the returns to schooling are higher than the corresponding OLS estimates. This result was interpreted as evidence for the existence for liquidity constraints. This paper is the first to provide direct evidence that the returns to education decline with family income or with parents' education and that this result is robust to various estimation methods, functional forms, age, labor market status and data sets.

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Table 1
Summary Statistics by Quintiles of Income per Capita Measured at Age 18

	Q1 (lowest)	Q2	Q3	Q4	Q5 (highest)
Panel A: Family Income and Education					
Log of Family Income Per Capita at Age 18	8.35	9.27	9.65	10.00	10.57
Father School Years	10.46	11.48	12.63	13.09	13.62
Mother School Years	10.66	11.65	12.37	12.47	12.92
Family Structure at Age 14					
Both Parents at Home at Age 14	0.67	0.74	0.84	0.92	0.92
Single Mother at Age 14	0.13	0.11	0.09	0.04	0.04
Number of Siblings	4.53	3.32	2.87	2.23	1.29
Location of Residence					
Currently					
North-East	0.09	0.17	0.19	0.28	0.20
North-Central	0.38	0.40	0.38	0.32	0.29
South	0.33	0.31	0.21	0.22	0.34
West	0.19	0.13	0.23	0.18	0.16
Lives in Smsa	0.71	0.74	0.78	0.83	0.85
In 1979 (First year of survey)					
North-East	0.11	0.18	0.22	0.30	0.24
North-Central	0.41	0.42	0.42	0.34	0.34
South	0.29	0.26	0.17	0.20	0.27
West	0.19	0.14	0.19	0.16	0.14
Lives in Smsa	0.54	0.60	0.69	0.69	0.77
Panel B: Educational Attainment					
School Years Completed	11.96	13.03	13.47	14.31	14.51
High-School Dropouts	0.32	0.23	0.16	0.07	0.05
High-School Graduates	0.43	0.35	0.33	0.32	0.31
Some College	0.15	0.21	0.23	0.20	0.22
College Graduates	0.06	0.11	0.17	0.24	0.23
Advanced Degree	0.04	0.11	0.12	0.17	0.20

Table 1 Continued

	Quintiles of income per Capita				
	Q1	**Q2**	**Q3**	**Q4**	**Q5**
<u>Panel C: Cognitive Achievements</u>					
AFQT(1989 Revision)	37.88	50.35	53.15	57.27	62.31
AFQT(1989 Revision) Adjusted for Age at Test	42.20	54.70	57.08	61.80	66.46
<u>Panel D: Behavioral Indicators</u>					
Behavioral Index^	5.67	4.73	5.54	5.36	4.72
<u>Alcohol and Drugs</u>					
Drank Alcohol	0.73	0.75	0.77	0.73	0.74
Used Marijuana	0.50	0.49	0.54	0.51	0.48
Used Other Drugs	0.22	0.20	0.22	0.21	0.19
Sold Marijuana	0.19	0.15	0.20	0.15	0.15
Sold Other Drugs	0.05	0.03	0.05	0.03	0.03
<u>Property Rights Violations</u>					
Shoplifted	0.31	0.31	0.33	0.32	0.33
Stole at a Value Over 50$	0.28	0.25	0.37	0.33	0.29
Stole at a Value Under 50$	0.10	0.09	0.09	0.12	0.05
Used Car W/O Owner's Permission	0.13	0.10	0.19	0.15	0.11
Broken into a Building	0.14	0.12	0.16	0.14	0.15
Sold Stolen Property	0.19	0.20	0.18	0.21	0.20
<u>Improper Behavior</u>					
Damaged Public Property With Intent	0.32	0.35	0.35	0.38	0.35
Skipped School	0.54	0.42	0.51	0.50	0.40
Ran Away From Home	0.13	0.03	0.11	0.03	0.07
Got into a Fight at School/Work	0.50	0.44	0.45	0.41	0.40
Seriously Threatened to Hit Someone	0.58	0.55	0.56	0.55	0.51
Used Force to Obtain Things	0.10	0.07	0.08	0.08	0.05
Attacked With Intent to Hurt/Kill	0.20	0.14	0.20	0.12	0.14

Table 1 Continued

	Quintiles of income per Capita				
	Q1	**Q2**	**Q3**	**Q4**	**Q5**
Other Illegal Behavior					
Had Some Illegal Income	0.27	0.19	0.26	0.24	0.17
Tried to Con Someone	0.30	0.22	0.31	0.29	0.28
Aided in a Gambling Operation	0.05	0.02	0.04	0.04	0.02
Clashes with the Law					
Ever Charged with a Crime	0.21	0.11	0.14	0.08	0.08
Ever Stopped by Police	0.32	0.23	0.35	0.31	0.26

Notes: The table provides summary statistics of individual characteristics and family background by quintiles of family income per capita measured at the time the individual was 18 years old.

^ Index of Behavior was calculated in the following way: For each individual we generated an indicator receiving the value 1 if this individual responded “yes” to the question about his behavior and 0 otherwise (The index ignores the number of times each behavior was conducted in the previous year) We then summed all the indicators for each individual. For example, if a person’s reported smoking marijuana 5 times in the past year, we added one to this person’s index.

Table 2
OLS Returns to Education

	Quintiles of Family Income Per Capita Measured at Age 18				
Controlling For:	Q1 (lowest)	Q2	Q3	Q4	Q5 (highest)
Panel A: Ages 25 and Above					
Individual Characteristics	**0.155**	**0.120**	**0.113**	**0.116**	**0.101**
	(0.025)	(0.026)	(0.026)	(0.026)	(0.024)
Individual and Family Characteristics	**0.195**	**0.119**	**0.100**	**0.115**	**0.074**
	(0.021)	(0.029)	(0.031)	(0.027)	(0.023)
Number of Observations	1804	1459	1473	1562	1680
<u>Working Full-Time Full Year</u>					
Individual and Family Characteristics	**0.188**	**0.120**	**0.107**	**0.112**	**0.067**
	(0.025)	(0.025)	(0.030)	(0.026)	(0.026)
Number of Observations	1213	1103	1086	1206	1309
Panel B: Ages 30-38					
Individual Characteristics	**0.174**	**0.140**	**0.117**	**0.087**	**0.080**
	(0.030)	(0.027)	(0.031)	(0.031)	(0.026)
Individual and Family Characteristics	**0.220**	**0.137**	**0.104**	**0.076**	**0.050**
	(0.026)	(0.029)	(0.037)	(0.034)	(0.027)
Number of Observations	878	710	728	752	809
<u>Working Full-Time Full Year</u>					
Individual and Family Characteristics	**0.204**	**0.153**	**0.105**	**0.090**	**0.041**
	(0.028)	(0.028)	(0.034)	(0.032)	(0.029)
Number of Observations	631	569	569	603	676

Notes: The table shows the coefficient on education from OLS regressions estimated for each sample (defined by: age, ftfy status etc) by family income per capita measured at the time the individual was 18 years old. In each regression the log of hourly wages was regressed on education and a set of individual characteristics (experience, experience squared, indicator for living in the south, smsa indicator and year dummies) and background variables (main and interactions effects of five groups of mother and father education, smsa in 1979, four dummies for region of residence in 1979, two indicators for both parents living at home at age 14 and living with a single mother).

Table 3
OLS Returns to Education
by Family Income Per Capita Measured at Age 18, Parents Education and AFQT Scores

	Sample is Partitioned into Five Groups by:				
Controlling For:	Q1(lowest)	Q2	Q3	Q4	Q5(highest)
Panel A: by Income Per Capita at Age 18					
Individual Characteristics	**0.174**	**0.140**	**0.117**	**0.087**	**0.080**
	(0.030)	(0.027)	(0.031)	(0.031)	(0.026)
Individual and Family Characteristics	**0.220**	**0.137**	**0.104**	**0.076**	**0.050**
	(0.026)	(0.029)	(0.037)	(0.034)	(0.027)
Number of Observations	878	710	728	752	809
Panel B: by Father and Mother Education					
See notes below for sample partition by parents education^					
Individual Characteristics	**0.160**	**0.137**	**0.122**	**0.080**	**0.085**
	(0.036)	(0.034)	(0.022)	(0.033)	(0.032)
Individual and Family Characteristics	**0.165**	**0.133**	**0.123**	**0.094**	**0.075**
	(0.037)	(0.035)	(0.022)	(0.030)	(0.033)
Number of Observations	616	827	1107	632	695
Panel C: by AFQT					
Individual Characteristics	**0.081**	**0.108**	**0.077**	**0.077**	**0.112**
	(0.034)	(0.031)	(0.029)	(0.031)	(0.028)
Individual and Family Characteristics	**0.077**	**0.108**	**0.056**	**0.082**	**0.112**
	(0.030)	(0.035)	(0.033)	(0.030)	(0.029)
Number of Observations	771	762	739	803	802

Notes: The table shows the coefficient on education from OLS regressions estimated for each sample (defined by: age, ftfy status etc) by family income per capita measured at age 18, by parents education and by AFQT scores. In each regression the log of hourly wages was regressed on education and a set of individual characteristics (experience, experience squared, indicator for living in the south, smsa indicator and year dummies) and background variables (main and interactions effects of five groups of mother and father education, smsa in 1979, four dummies for region of residence in 1979, two indicators for both parents living at home at age 14 and living with a single mother).

^ We divided parents' education into five groups as follows: (Q1) both parents have less than 12 years of schooling (Q2) one parent has at least 12 years of schooling and the other parent has less than 12 years of schooling (Q3) both parents have 12 years of schooling (Q4) one parent has more than 12 years of schooling and the other parent has 12 years of schooling and (Q5) both parents have more than 12 years of schooling.

Table 4

Relationship Between School Years Completed AFQT Scores and Non-Cognitive Behavior^

	Quintiles of Family Income per Capita Measured at Age 18:									
	Without Controls					**With Background Controls**				
Variables	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Panel A: AFQT										
AFQT	**0.046**	**0.053**	**0.057**	**0.067**	**0.069**	**0.042**	**0.045**	**0.047**	**0.059**	**0.047**
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)	(0.007)	(0.005)	(0.007)
Panel B: Index of Behavior										
Index of Non-Cognitive Behavior	**-0.084**	**-0.172**	**-0.146**	**-0.087**	**-0.156**	**-0.114**	**-0.157**	**-0.138**	**-0.081**	**-0.082**
	(0.028)	(0.039)	(0.040)	(0.038)	(0.041)	(0.029)	(0.038)	(0.042)	(0.036)	(0.036)
Panel C: AFQT and Index of Behavior										
AFQT	**0.045**	**0.050**	**0.055**	**0.067**	**0.067**	**0.040**	**0.042**	**0.045**	**0.059**	**0.046**
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.007)
Index of Non-Cognitive Behavior	**-0.065**	**-0.111**	**-0.113**	**-0.070**	**-0.097**	**-0.091**	**-0.122**	**-0.114**	**-0.074**	**-0.069**
	(0.024)	(0.032)	(0.031)	(0.028)	(0.035)	(0.024)	(0.033)	(0.034)	(0.029)	(0.034)
Number of Individuals	241	198	195	201	235	241	198	195	201	235

Notes: The table reports the coefficients on AFQT and/or Index of Behavior from an OLS regression of education on AFQT and/or the Index of Behavior, by family income per capita measured at age 18. Each panel shows the coefficient in a regression without controls and with a set of controls that include parents' education, age and age-squared, family structure at age 14 and dummies for region of residence in 1979.

^ Index of Behavior was calculated in the following way: For each individual we generated an indicator receiving the value 1 if this individual responded "yes" to the question about his behavior and 0 otherwise (The index ignores the number of times each behavior was conducted in the previous year) We then summed all the indicators for each individual. For example, if a person's reported smoking marijuana 5 times in the past year, we added one to this person's index.

Table 5
OLS Returns to Education Controlling for AFQT and Index of Behavior^

	Quintiles of Family Income per Capita at Age 18:									
	With Individual Controls					**With Individual and Family Controls**				
Variables	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Panel A: AFQT										
Education	**0.137**	**0.110**	**0.074**	**0.058**	**0.061**	**0.176**	**0.113**	**0.069**	**0.055**	**0.041**
	(0.031)	(0.030)	(0.033)	(0.030)	(0.029)	(0.027)	(0.031)	(0.036)	(0.033)	(0.027)
AFQT	**0.392**	**0.348**	**0.572**	**0.415**	**0.373**	**0.474**	**0.277**	**0.585**	**0.353**	**0.319**
	(0.118)	(0.161)	(0.154)	(0.176)	(0.177)	(0.132)	(0.152)	(0.180)	(0.191)	(0.183)
Panel B: Index of Behavior										
Education	**0.163**	**0.147**	**0.123**	**0.094**	**0.077**	**0.216**	**0.148**	**0.116**	**0.080**	**0.053**
	(0.029)	(0.028)	(0.033)	(0.032)	(0.028)	(0.026)	(0.029)	(0.039)	(0.036)	(0.029)
Index of Non-Cognitive Behavior	**-0.097**	**0.069**	**0.061**	**0.072**	**-0.041**	**-0.026**	**0.138**	**0.117**	**0.032**	**0.038**
	(0.083)	(0.076)	(0.087)	(0.080)	(0.081)	(0.080)	(0.088)	(0.097)	(0.081)	(0.090)
Panel C: AFQT and Index of Behavior										
Education	**0.125**	**0.117**	**0.078**	**0.064**	**0.056**	**0.170**	**0.125**	**0.078**	**0.056**	**0.044**
	(0.031)	(0.030)	(0.036)	(0.032)	(0.030)	(0.029)	(0.031)	(0.039)	(0.035)	(0.029)
AFQT	**0.399**	**0.348**	**0.566**	**0.405**	**0.376**	**0.477**	**0.277**	**0.567**	**0.350**	**0.317**
	(0.119)	(0.160)	(0.155)	(0.174)	(0.177)	(0.134)	(0.151)	(0.179)	(0.194)	(0.182)
Index of Non-Cognitive Behavior	**-0.105**	**0.070**	**0.035**	**0.056**	**-0.048**	**-0.039**	**0.137**	**0.084**	**0.009**	**0.034**
	(0.077)	(0.075)	(0.086)	(0.076)	(0.079)	(0.075)	(0.084)	(0.094)	(0.081)	(0.088)
Number of Individuals	878	710	728	752	809	878	710	728	752	809

Notes: The tables reports the coefficients on education, AFQT and Index of Behavior from an OLS regression of log hourly wage on AFQT and/or the Index of Behavior, by family income per capita measured at age 18. Each panel shows the coefficient from a regression with controls for individual characteristics (experience, experienced squared, indicator for living in the south, smsa indicator and year dummies) and also with controls for background variables (main and interacted effects of five groups of mother and father education, smsa in 1979, four dummies for region of residence in 1979, two indicators for both parents living at home at age 14 and living with a single mother.

^ Index of Behavior was calculated in the following way: For each individual we generated an indicator receiving the value

1 if this individual responded “yes” to the question about his behavior and 0 otherwise (The index ignores the number of times each behavior was conducted in the previous year) We then summed all the indicators for each individual. For example, if a person’s reported smoking marijuana 5 times in the past year, we added one to this person’s index.

Table 6
The Effects of Parental Education and AFQT on Wages and the Education Slope
Repeating Altonji and Dunn(1996)

See notes below for sample partition by parents education^

	With Family Fixed-Effects			
Panel A: Using Altonji and Dunn's Specification for Parents' education^				
Education	**9.52**	**9.15**	**6.84**	**6.48**
	(1.99)	(3.47)	(2.63)	(3.88)
Mother's Educ.	**1.10**	**0.66**	**1.11**	**0.67**
x Education	(0.61)	(0.58)	(0.61)	(0.58)
Father's Educ.	**-1.78**	**-1.67**	**-1.77**	**-1.66**
x Education	(0.38)	(0.39)	(0.38)	(0.39)
Mother's Educ.				
Father's Educ.				
AFQT		0.34		0.34
		(0.11)		(0.11)
AFQT x Educ.		0.05		0.05
		(0.05)		(0.05)
Experience			0.20	0.20
x Education			(0.13)	(0.12)
R-squared	0.153	0.156	0.153	0.157
Panel B: Using Two Groups of Parents' Education^				
Education	**10.32**	**8.75**	**7.55**	**6.02**
	(2.39)	(3.82)	(2.89)	(4.15)
Paretnt's Educ.	**-5.27**	**-4.82**	**-5.28**	**-4.83**
x Education	(2.89)	(2.88)	(2.89)	(2.88)
Paretnt's Educ.	.	.	.	.
	.	.	.	.
AFQT		0.40		0.39
		(0.11)		(0.11)
AFQT x Educ.		0.03		0.03
		(0.05)		(0.05)
Experience			0.20	0.21
x Education			(0.13)	(0.13)
R-squared	0.149	0.153	0.15	0.154

Notes: The table reports the coefficients from an OLS regression with family fixed-effects of log hourly wage on own education, main effects and interactions (with own education) of parents' education, AFQT and potential experience. Additional controls in each regression are individual characteristics (experience, experienced squared, indicator for living in the south, smsa indicator and year dummies) and controls for background variables (main and interacted effects of five groups of mother and father education, smsa in 1979, four dummies for region of residence in 1979, two indicators for both parents living at home at age 14 and living with a single mother.

^ In panel (A) we follow Altonji and Dunn and introduce mother and father's education separately. In Panel (B) parents' education is introduced as an indicator variable that receives the value "zero" for the Low group and the value of "one" for the High group. The Low/High groups are defined as follows: (Low group) both parents have less than 12 years of schooling, one parent has at least 12 years of schooling and the other parent has less than 12 years of schooling, both parents have 12 years of schooling and (High group) one parent has more than 12 years of schooling and the other parent has 12 years of schooling, both parents have more than 12 years of schooling.

Table 7
OLS and IV (Proximity to College) Returns to Education and to College, by Parents Education

See notes below for sample partition by parents education^

	OLS Estimation		IV Estimation			
			2SLS		LIML	
Parents' Education:	Low	High	Low	High	Low	High
Panel A: Returns to Schooling						
	0.072	**0.052**	**0.151**	**0.097**	**0.184**	**0.121**
	(0.006)	(0.008)	(0.052)	(0.045)	(0.079)	(0.071)
Weak Identification Test Kleibergen-Paap rk Wald F statistic			3.097	3.647	3.097	3.647
Hansen J Statistic P-value			0.117	0.207	0.179	0.261
Number of Observations	10511	5378	10511	5378	10511	5378
Panel B: Returns to College						
	0.344	**0.262**	**0.774**	**0.251**	**0.860**	**0.243**
	(0.037)	(0.036)	(0.255)	(0.241)	(0.314)	(0.410)
Weak Identification Test Kleibergen-Paap rk Wald F statistic			4.270	13.020	4.270	13.020
Hansen J Statistic P-value			0.175	0.0733	0.203	0.0724
Number of Observations	10511	5378	10511	5378	10511	5378

Table 8
OLS and IV (Quarter of Birth) Returns to Education and to College, by Parents Education

See notes below for sample partition by parental education^

	OLS Estimation		IV Estimation 2SLS		IV Estimation LIML	
Parents' Education:	Low	High	Low	High	Low	High
Panel A: Returns to Schooling						
Education	**0.080**	**0.054**	**0.112**	**0.066**	**0.141**	**0.076**
	(0.005)	(0.007)	(0.032)	(0.042)	(0.063)	(0.082)
Weak Identification Test Kleibergen-Paap rk Wald F statistic			2.087	0.806	2.087	0.806
Hansen J Statistic P-value			0.0974	0.763	0.151	0.767
Number of Observations	9845	5040	9845	5040	9845	5040
Panel B: Returns to College						
College	**0.377**	**0.278**	**0.428**	**0.063**	**0.630**	**-0.178**
	(0.035)	(0.034)	(0.227)	(0.204)	(1.141)	(0.472)
Weak Identification Test Kleibergen-Paap rk Wald F statistic			1.843	0.926	1.843	0.926
Hansen J Statistic P-value			0.0191	0.711	0.0309	0.838
Number of Observations	9845	5040	9845	5040	9845	5040

Notes: The table reports the coefficients from a 2SLS estimation of log hourly wage on education, estimated for two groups of parents' education separately. We follow the specification presented in Angrist and Krueger (1991), Table 7 pp-1003.

^ We divided parents education into two groups as follows: (Low group) both parents have less than 12 years of schooling, one parent has at least 12 years of schooling and the other parent has less than 12 years of schooling, both parents have 12 years of schooling and (High group) one parent has more than 12 years of schooling and the other parent has 12 years of schooling, both parents have more than 12 years of schooling.

Table 9
Local Average Effects (OLS)

Parents' Education^	Low		High	
AFQT Group	Low	High	Low	High
Group Statistics				
Fraction with College Degree	0.03	**0.28**	**0.26**	0.76
Average School Years (COL=1)	11.37	**12.45**	**12.40**	13.43
Average School Years (COL=0)	16.23	**16.61**	**16.56**	17.03
School Years Completed	11.50	**13.61**	**13.50**	16.17
Father's School Years	10.07	**11.12**	**15.01**	16.02
Mother's School Years	10.73	**11.37**	**13.58**	14.16
Age-Adjusted AFQT	26.74	**72.25**	**50.84**	88.94
Index of Behavior^^	5.03	**4.26**	**5.18**	3.78
Number of Observations	5046	5027	2579	2575
Panel A: School Years Completed				
Coefficient on:				
College from an OLS Regression	**0.075**		**0.053**	
	(0.006)		(0.008)	
School Years from an OLS Regression	0.068	**0.065**	**0.050**	0.039
	(0.011)	(0.008)	(0.012)	(0.013)
School Years from an OLS Regression	0.054	**0.057**	**0.039**	0.027
Controlling for AFQT	(0.012)	(0.009)	(0.013)	(0.014)
Panel B: College Graduation				
Coefficient on:				
College from an OLS Regression	**0.356**		**0.269**	
	(0.037)		(0.036)	
College from an OLS Regression	0.112	**0.313**	**0.241**	0.216
	(0.103)	(0.041)	(0.057)	(0.059)
College from an OLS Regression	0.031	**0.271**	**0.196**	0.181
Controlling for AFQT	(0.101)	(0.046)	(0.058)	(0.060)

Notes: ^The Low/High groups of parents' education are defined as follows: (Low group) both parents have less than 12 years of schooling, one parent has at least 12 years of schooling and the other parent has less than 12 years of schooling, both parents have 12 years of schooling and (High group) one parent has more than 12 years of schooling and the other parent has 12 years of schooling, both parents have more than 12 years of schooling.

Table W1
OLS Returns to Education

	Quintiles of Family Income Measured at Age 18				
Controlling For:	Q1 (lowest)	Q2	Q3	Q4	Q5 (highest)
Panel A: Ages 25 and Above					
Individual Characteristics	**0.146**	**0.083**	**0.099**	**0.116**	**0.107**
	(0.021)	(0.031)	(0.032)	(0.024)	(0.022)
Individual and Family Characteristics	**0.156**	**0.096**	**0.094**	**0.093**	**0.107**
	(0.021)	(0.040)	(0.035)	(0.024)	(0.022)
Number of Observations	2113	1234	1286	1698	1647
Working Full-Time Full Year (Age 25+)					
Individual and Family Characteristics	**0.156**	**0.086**	**0.082**	**0.097**	**0.093**
	(0.021)	(0.038)	(0.038)	(0.024)	(0.025)
Number of Observations	1447	916	956	1335	1263
Panel B: Ages 30-38					
Individual Characteristics	**0.156**	**0.077**	**0.100**	**0.111**	**0.095**
	(0.024)	(0.034)	(0.037)	(0.030)	(0.025)
Individual and Family Characteristics	**0.175**	**0.092**	**0.102**	**0.084**	**0.082**
	(0.024)	(0.044)	(0.041)	(0.030)	(0.026)
Number of Observations	1008	614	634	817	804
Working Full-Time Full Year (Age 38+)					
Individual and Family Characteristics	**0.172**	**0.074**	**0.089**	**0.095**	**0.074**
	(0.024)	(0.040)	(0.046)	(0.028)	(0.028)
Number of Observations	748	476	492	672	660

Notes: The table shows the coefficient on education from OLS regressions estimated for each sample (defined by: age, ftfy status etc) by family income per capita measured at the time the individual was 18 years old. In each regression the log of hourly wages was regressed on education and a set of individual characteristics (experience, experience squared, indicator for living in the south, smsa indicator and year dummies) and background variables (main and interactions effects of five groups of mother and father education, smsa in 1979, four dummies for region of residence in 1979, two indicators for both parents living at home at age 14 and living with a single mother).

Table W2
OLS Returns to Education Controlling for AFQT and Index of Behavior

	Medians of Income Per capita at Age 18									
Controlling For:^	Low	High	Low	High	Low	High	Low	High	Low	High
Years of Schooling	**0.144**	**0.095**	**0.154**	**0.083**	**0.118**	**0.059**	**0.155**	**0.084**	**0.117**	**0.060**
	(0.018)	(0.018)	(0.019)	(0.019)	(0.021)	(0.019)	(0.019)	(0.021)	(0.021)	(0.021)
AFQT					**0.414**	**0.452**			**0.414**	**0.452**
					(0.098)	(0.110)			(0.098)	(0.110)
Index of Non-Cognitive Behavior							**0.119**	**0.121**	**-0.020**	**0.052**
							(0.508)	(0.529)	(0.498)	(0.513)
Individual Characteristics	Yes		Yes		Yes		Yes		Yes	
Family Characteristics			Yes		Yes		Yes		Yes	
Number of Observations	1947	1930	1947	1930	1947	1930	1947	1930	1947	1930

Notes: The tables reports the coefficients on education, AFQT and Index of Behavior from an OLS regression of log hourly wage on AFQT and/or the Index of Behavior, by family income per capita measured at age 18. Each panel shows the coefficient from a regression with controls for individual characteristics (experience, experienced squared, indicator for living in the south, smsa indicator and year dummies) and also with controls for background variables (main and interacted effects of five groups of mother and father education, smsa in 1979, four dummies for region of residence in 1979, two indicators for both parents living at home at age 14 and living with a single mother.

^ Index of Behavior was calculated in the following way: For each individual we generated an indicator receiving the value 1 if this individual responded "yes" to the question about his behavior and 0 otherwise (The index ignores the number of times each behavior was conducted in the previous year) We then summed all the indicators for each individual. For example, if a person's reported smoking marijuana 5 times in the past year, we added one to this person's index.

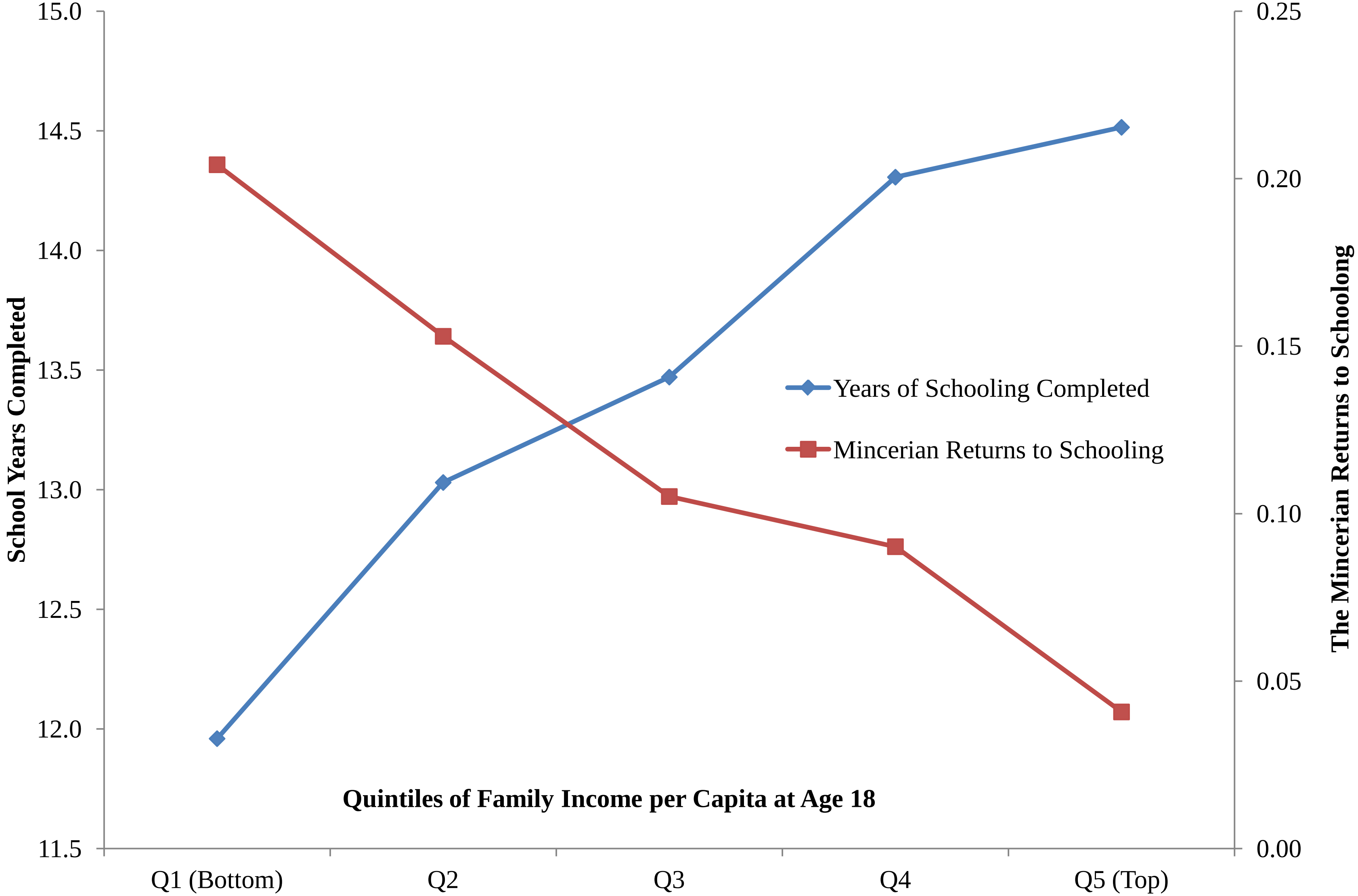

Figure 1
The Mincerian Returns to Schooling and School Years Completed by Quintiles of Family Income per Capita at Age 18

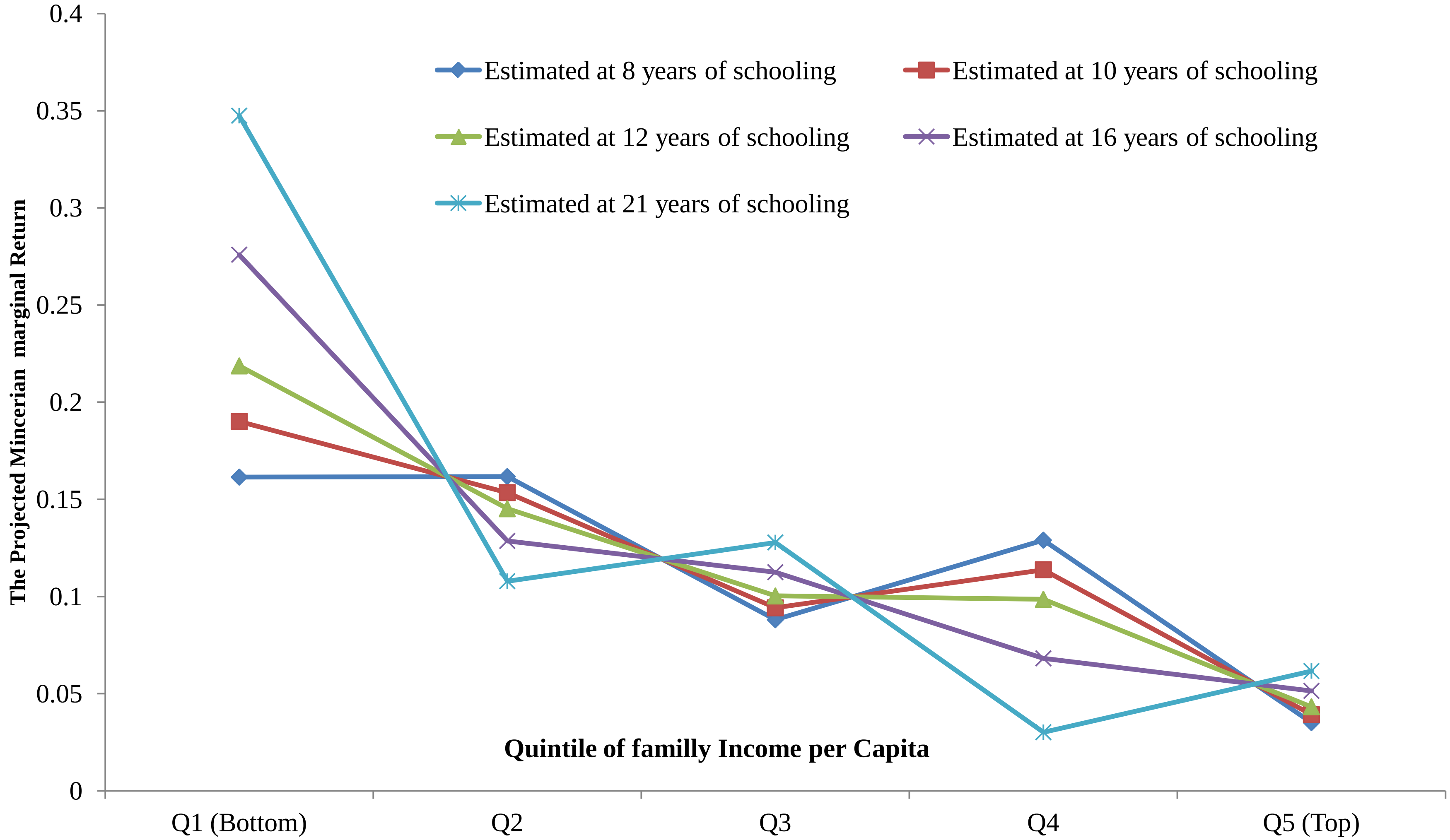

Figure 2a
The Mincerian Marginal Returns to Schooling ,
by Quintiles of Family Income per Capita at Age 18

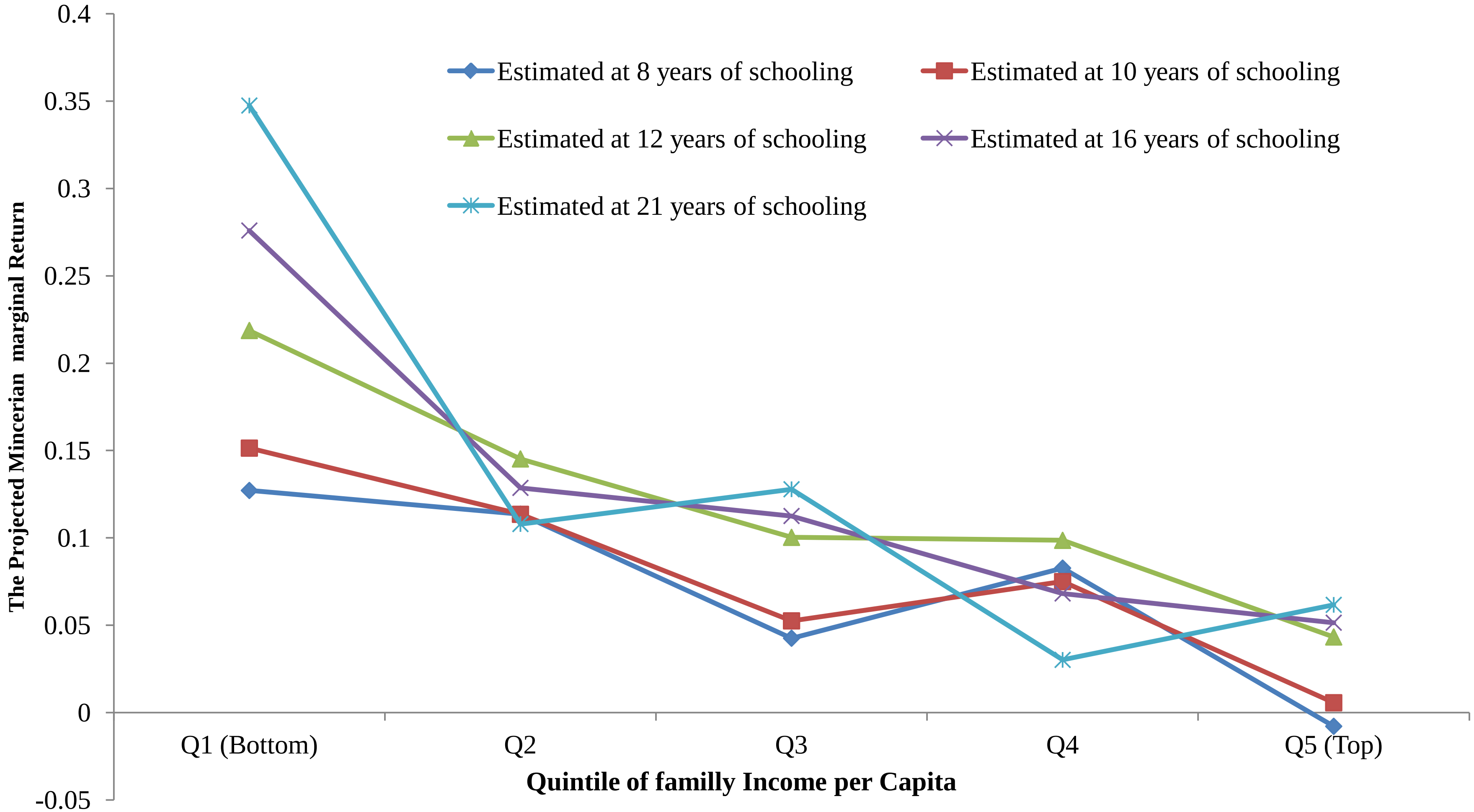

Figure 2b
The Mincerian Marginal Returns to Schooling Controlling for AFQT and Index of Behavior,
by Quintiles of Family Income per Capita at Age 18

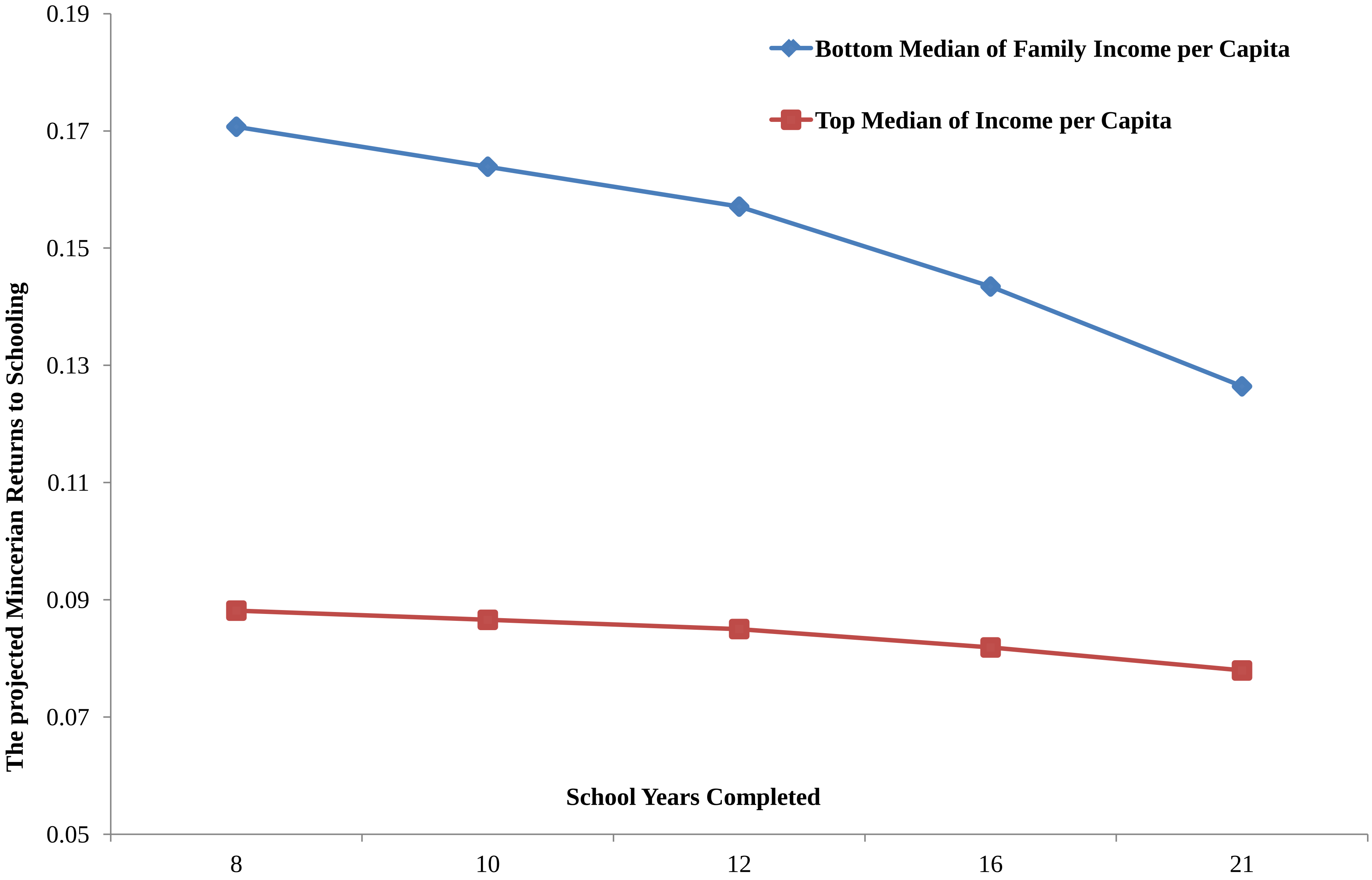

Figure W1
The Mincerian Marginal Return to School Years Completed, by Medians of Family Income per Capita at Age 18