Testing for Educational Credit Constraints using Heterogeneity in Individual Time Preferences

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Abstract

I develop a model in which individual time discount rates have a larger effect on human capital accumulation when credit constraints are binding. Impatient individuals obtain less schooling when borrowing constraints limit the ability to finance consumption during school. Using data from the NLSY79 in which race and family income serve as proxies for family wealth and access to formal credit, I show that self-reported measures of time preferences have a significantly higher effect on the college attendance decisions of blacks than those of whites and the decisions of low-income youths than those of high-income youths. These results provide new evidence that members of disadvantaged groups obtain lower levels of schooling because they are credit constrained.
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1 Introduction

Do young people underinvest in human capital because they have difficulty obtaining funding to support their education? Answering this question is complicated by the fact that identifying liquidity-constrained individuals is difficult with standard data sources. Economists have developed a variety of indirect methods for determining the extent to which a lack of credit affects human-capital investment, but there is significant debate about this question in the literature: as described in Lochner and Monge-Naranjo (2012), many studies in this literature find little evidence that credit constraints have a major impact on schooling decisions (e.g. Cameron and Heckman, 1998; Keane and Wolpin, 2001; Carneiro and Heckman, 2002; Cameron and Taber, 2004; Stinebrickner and Stinebrickner, 2008), while others find or imply that credit constraints play a much more substantive role (Card, 1999; Ellwood and Kane, 2000; Belley and Lochner, 2007; Brown, Scholz, and Seshadri, 2012; Lovenheim, 2011).[1]

This paper introduces a new method for examining educational borrowing constraints based on the relationship between individual time discount rates and schooling investments in a simple human-capital model. While many papers focus on the potential inability of constrained individuals to pay the *direct* costs of attending school (e.g. tuition), a key insight that has been brought out in recent papers (Lochner and Monge-Naranjo, 2011; Stinebrickner and Stinebrickner, 2008) is that if youths are credit constrained, they will have difficulty smoothing consumption while they are students.[2] Using consumption data

[1]Lochner and Monge-Naranjo (2012) do conclude that part of the discrepancy in findings on the importance of borrowing constraints is due to differences in the time period covered by various data sources, with studies using more recent data generally finding a larger role for borrowing constraints.

[2]Johnson (2013) finds that borrowing constraints are tight for most students, implying low levels of consumption, but argues that youths would not borrow substantially more if constraints were relaxed due

from the Consumer Expenditure Survey, Fernandez-Villaverde and Krueger (2007) find that college-educated individuals' expenditures rise much more steeply after age 22 than do the expenditures of those with a high-school diploma or less.[3] The extent to which this acts as a deterrent to post-secondary education is potentially salient given that (i) government grant and loan programs are not designed to replace "non-schooling" consumption while individuals are in school (Lochner and Monge-Naranjo, 2011) (so that enrollees must rely on family aid or private liquidity to more fully smooth consumption while they are in school) and (ii) some youths may not act as perfectly time-consistent agents, instead placing increased emphasis on current consumption to the detriment of their future selves (Laibson, 1997; DellaVigna, 2009).[4] Thus, in the absence of parental transfers or private lending, some individuals may underinvest in schooling because of their distaste for "lean" consumption during their college years.

In this paper, I present a model of human-capital investment and show that individual time discount rates have a larger effect on the probability of college attendance when credit constraints (in the form of a fixed limit on borrowing) are binding. I then use data from the National Longitudinal Survey of Youth, 1979 cohort (NLSY79), which contains a measure of individual time preference based on self-reported data, to examine the relationship between

to uncertainty associated with future earnings.

[3] See Figure 7 of Fernandez-Villaverde and Krueger (2007).

[4] Under federal student loan programs, "students (or parents) can borrow only up to the total cost of college (including tuition, room, board, books, computers, and other expenses directly related to schooling) less any other financial aid they receive in the form of grants or scholarships" (Lochner and Monge-Naranjo, 2011, pg. 2495). Students from poor backgrounds may act constrained even if they do not reach formal financial aid limits. Students from wealthy and/or more generous families may enjoy informal gifts or loans for which repayment is either not expected or contingent on future outcomes. Since federal and private loans must be repaid (importantly, student loan debt cannot easily be discharged in the case of bankruptcy) to avoid harsh penalties, some students may wish to limit debt for fear of not succeeding in or after college. Short of informal family aid to help supplement consumption, the prospect of more frugal conditions during school will be relatively more appealing to youths who value the future highly.

schooling and discount rates.[5] I establish that patience (as measured by how willing individuals are to forego a current prize for a future one, hypothetically) is significantly (positively) correlated with college attendance even after conditioning on a host of individual and family characteristics (including family income at age 17, test scores, and parental education). However, time preferences as measured in the NLSY79 may reflect unobserved qualities that are themselves correlated with youths' college choices (e.g. home environment), implying that these estimates suffer from omitted variable bias. Furthermore, causality may run in the opposite direction, whereby educated individuals are more likely to develop patience as a result of their schooling (Becker and Mulligan, 1997). As a result of these issues, I focus not on the effect of time preferences on schooling for the population as a whole but rather on how the relationship between time preferences and college attendance varies with respect to family resources and race.

Because individuals with greater family income/wealth are less likely to find an upper limit on borrowing to be binding (all else equal), the effect of time preference on schooling should be particularly strong for youths who come from more disadvantaged families. Indeed, youths whose parents have means (and the desire to support their child in school) will have the least difficulty smoothing consumption during school. On the other hand, youths from families of lower means are particularly susceptible to low consumption during school (given the lack of low-risk options to support such consumption), meaning that patience is likely to play a larger role in the college decisions of this group. My results are consistent with these predictions: the effect of patience on college attendance diminishes as family income

[5] Courtemanche, Heutel, and McAlvanah (2014) use the same measure of time preference in their study of obesity and food prices. They show that more impatient individuals are more likely to be obese and are more sensitive to changes in food prices.

increases. Furthermore, although family wealth is not contained in the NLSY79, I examine the effects by race/ethicity, given that it has been demonstrated that blacks hold lower levels of wealth (e.g. Barsky et al., 2002) and may have less access to private credit (e.g. Ladd, 1998) than do whites.[6] I find that time preferences play an economically and statistically significant role in the probability of black (and, to some extent, Hispanic) college attendance but very little role in the attendance decisions of whites.

By comparing differences in the effect of patience on college attendance by race and family income, concerns regarding the endogeneity of time preferences are mitigated. Any bias resulting from omitted variables is not a threat to identification unless the effect of unobservables differs systematically by race and family income (a possibility I discuss in Section 4.2). Because it is not clear why, for example, a home environment that places emphasis on delayed gratification would lead to increased schooling for blacks or Hispanics (or low-income youths) but not for whites (or high-income youths) for a reason other than the ability to obtain family and/or private support while in college, I conclude that credit constraints play a meaningful role in the college decisions of underprivileged youth.

My results indicate that a 1 standard deviation increase in the discount factor (the measure of patience used in this paper, as described in Section 3) results in a 6 percentage point increase in the probability of attending college among blacks but less than a 1 percentage point increase in the same probability among whites. Similarly, youths in the lowest family income tercile experience a 4 percentage point increase in the probability of attendance when

[6] On the first point, Barsky et al. (2002, pg. 664) states that, "among the middle-aged, 90% of black households have less wealth than the median white household even after controlling for the earnings differential." On the second point, Cheng et al. (2014) find that with respect to mortgage interest rates, "black borrowers on average pay about 29 basis points more than comparable white borrowers," with an even larger discrepancy for black women.

the discount factor rises by 1 standard deviation, but the increase is only slightly more than 1 percentage point among youths in the highest tercile. By comparing enrollment percentages among youths with the most patient preferences to youths with lower discount factors, I find that 6.5 percent of blacks and 5.5 percent of low-income youths in the NLSY79 do not attend college due to constraints on their ability to smooth consumption while in school. I discuss these figures in the context of the literature in Section 5.

2 Model

Consider a two-period model in which individuals make a discrete choice to attend college ($S = 1$) or not ($S = 0$) in the first period. Individuals maximize their lifetime utility, which is given by

$$U_S = \frac{c_{S,1}^{\gamma}}{\gamma} + \beta \frac{c_{S,2}^{\gamma}}{\gamma} - v(S), \tag{1}$$

where γ is a parameter of utility curvature with a value in $(-\infty, 1)$.[7] $c_{S,1}$ represents first-period consumption (at schooling level S), $c_{S,2}$ is second-period consumption (at schooling level S), and β is an individual's time discount factor (with $0 < \beta \leq 1$). $v(S)$ represents nonpecuniary tastes for schooling level S. The first and second-period budget constraints of an individual who attends college are given by:

[7] Other papers in the human capital literature have also used CRRA preferences (for example, Cameron and Taber, 2004).

$$c_{1,1} = \omega + d - \tau \tag{2}$$

$$c_{1,2} = y_{1,2} - Rd. \tag{3}$$

ω represents the individual's endowment (e.g. from one's family), d represents debt the individual holds in period 1 (with a negative value representing savings), and τ is the direct cost associated with college attendance. I assume that individuals cannot work while attending college. $y_{1,2}$ is second-period earnings if the individual goes to school. The gross risk-free interest rate is R. The constraints faced by an individual who does not attend college are:

$$c_{0,1} = \omega + d + y_{0,1} \tag{4}$$

$$c_{0,2} = y_{0,2} - Rd. \tag{5}$$

$y_{0,1}$ and $y_{0,2}$ are first and second-period earnings, respectively, if the individual does not go to school. In the context of this model, I consider two scenarios: one in which individuals can borrow (and save) freely, and one in which borrowing is constrained at some level ($\bar{d}$). I consider the unconstrained case first. Consumption in each period is given by:

$$c^*_{S,1} = \frac{z_S}{1 + \beta^{\frac{1}{1-\gamma}} R^{\frac{\gamma}{1-\gamma}}} \tag{6}$$

$$c^*_{S,2} = (\beta R)^{\frac{1}{1-\gamma}} c^*_{S,1} \tag{7}$$

z_S represents lifetime wealth under each state of world: if the individual attends school ($S = 1$), $z_1 = \omega - \tau + \frac{y_{1,2}}{R}$; if the individual does not attend school ($S = 0$), $z_0 = \omega + y_{0,1} + \frac{y_{0,2}}{R}$. The individual chooses $S = 1$ when $U_1 > U_0$ and $S = 0$ otherwise. For simplicity, I assume that $v(1) - v(0) = v \geq 0$ (attending school is distasteful). v, which is unobserved by the analyst, is assumed to be randomly distributed in the population. Conditional on other variables in the model (discount factor, wages in each state of the world, one's endowment, interest rate, and direct schooling costs), the probability that the individual attends school is:

$$Pr(S = 1|\beta, \omega, \tau, R, y_{0,1}, y_{0,2}, y_{1,2}) = Pr(v < D^{unc}|\beta, \omega, \tau, R, y_{0,1}, y_{0,2}, y_{1,2}), \tag{8}$$

where

$$D^{unc} = (\frac{z_1^{\gamma}}{\gamma} - \frac{z_0^{\gamma}}{\gamma})(1 + \beta^{\frac{1}{1-\gamma}} R^{\frac{\gamma}{1-\gamma}})^{1-\gamma}). \tag{9}$$

If there is no disutility associated with schooling ($v = 0$), the individual simply makes the schooling choice that maximizes lifetime income. This provides the well-known result that in the absence of credit constraints, human-capital investments do not depend on individual time preferences (Becker, 1967 and Fuchs, 1982) because investment and consumption decisions are effectively separated. If $v > 0$, D^{unc} rises with β because z_1 must be greater than z_0 (otherwise no one would attend college). This implies college attendance is more likely at higher levels of β. Intuitively, those with more patient preferences do not mind the disutility of schooling (realized in the first period) as much as those who value the present more heavily.[8]

I now examine the predictions of the model when the maximum debt an individual can hold if he goes to college is $\bar{d}$.[9] If an individual is constrained at the maximum, then consumption in each period under the college state of the world is simply:

$$c_{1,1} = \omega + \bar{d} - \tau \tag{10}$$

$$c_{1,2} = y_{1,2} - R\bar{d} \tag{11}$$

Such individuals will attend college if:

$$Pr(S = 1|\beta, \omega, \tau, R, y_{0,1}, y_{0,2}, y_{1,2}) = Pr(v < D^{con}|\beta, \omega, \tau, R, y_{0,1}, y_{0,2}, y_{1,2}), \tag{12}$$

where

$$D^{con} = \frac{(\omega + \bar{d} - \tau)^{\gamma}}{\gamma} + \beta\frac{(y_{1,2} - R\bar{d})^{\gamma}}{\gamma} - \frac{z_0^{\gamma}}{\gamma}(1 + \beta^{\frac{1}{1-\gamma}} R^{\frac{\gamma}{1-\gamma}})^{1-\gamma}. \tag{13}$$

[8]If schooling provides positive rather than negative utility, this prediction is reversed (β is negatively related to college attendance). However, as shown below, it is still the case that the effect of β on schooling is relatively more positive when credit constraints are introduced into the model.

[9]In the model presented in the paper, I do not assume that borrowing is restricted in the case that the individual does not attend school. This is for two reasons: first, optimal borrowing when $S = 0$ is lower (given the ability to work in the first period) than when $S = 1$ such that any borrowing limit is less likely to bind. Second, loans made for human-capital investments are not collateralized, while typical loans for consumption (housing, cars) are collateralized, so educational borrowing limits likely do not apply to common loans for non-students. Notwithstanding these arguments, I also consider the possibility of a single fixed borrowing limit binding both when $S = 0$ and $S = 1$. Since the limit should bind more "tightly" when $S = 1$, I expect that all results presented below hold even when this is the case. Unfortunately, a closed-form solution to the inequality in Equation (14) is not available under general CRRA preferences. However, under a simplified utility structure (log utility, or $\gamma = 0$), Proposition 1 is true for any non-negative borrowing limit (result available upon request). When the constraint binds in both states of the world, the steepness of the lifetime income profile under $S = 0$ affects how many youths avoid college because they are consumption constrained. Examining this implication is left to future work.

For individuals who are constrained at $\bar{d}$, a desire to increase lifetime earnings by attending college must be balanced against the desire to smooth consumption between periods. The prospect of lowering first-period consumption in order to attend college is more palatable to youths with a greater degree of patience. Thus, the positive effect of β on D^{con} is even larger than it is on D^{unc}:

Proposition 1. *The effect of β on the difference in utility between attending college and not attending college is larger when an individual is constrained at debt level $\bar{d}$ than when an individual is unconstrained:*

$$\frac{\partial D^{con}}{\partial \beta} - \frac{\partial D^{unc}}{\partial \beta} > 0. \tag{14}$$

The proof is contained in Appendix A.

This simple model predicts that discount factors will have a larger effect on schooling if individuals are credit constrained. For empirical estimation, I model the probability of attending college for both the constrained and unconstrained groups:

$$Pr(D^{unc} - v > 0 | \beta, \omega, \tau, R, y_{0,1}, y_{0,2}, y_{1,2}) \approx Pr(S = 1 | X, DF)^{unc} = Pr(\lambda_1 DF + X\eta_1 - \epsilon_1 > 0 | X, DF) \tag{15}$$

and

$$Pr(D^{con} - v > 0 | \beta, \omega, \tau, R, y_{0,1}, y_{0,2}, y_{1,2}) \approx Pr(S = 1 | X, DF)^{con} = Pr(\lambda_2 DF + X\eta_2 - \epsilon_2 > 0 | X, DF), \quad (16)$$

where DF is a proxy for time preference β (described in the next section), X is a vector of observable individual and family characteristics, λ_1, η_1, λ_2, and η_2 are parameters to be estimated, and ϵ_1 and ϵ_2 are unobservable characteristics (such as schooling tastes). My main focus is testing whether the marginal effect of DF on $Pr(S = 1|X)^{con}$ is greater than its effect on $Pr(S = 1|X)^{unc}$ by modeling these as probit specifications or linear probability models.

In Section 3, I discuss the specific control variables available in my data that are likely related to a youth's earnings profile in each state of the world, her endowment, direct college costs, and interest rate. Some aspects of the schooling decision obviously remain unobserved (such as schooling tastes). When will this pose a problem for recovery of the difference in the effect of time preference on college attendance for constrained and unconstrained groups? Assuming perfect proxies for time preference and which individuals are credit constrained, the issue concerns whether unobservables are differentially correlated with time preferences for the constrained and unconstrained groups.[10] This can most easily be seen in the linear probability model:

$$S_j = \lambda_j DF + X\eta_j + \epsilon_j, \quad (17)$$

[10]The issue of measurement error in the time-preference proxy is discussed in Section 3.2.

where $j = 1$ for the unconstrained group and $j = 2$ for the constrained group.[11] The OLS estimator of λ converges in probability to the true parameter plus an asymptotic bias term:

$$\hat{\lambda}_{jOLS} \xrightarrow{p} \lambda_j + \frac{cov(\widetilde{DF}_j, \widetilde{\epsilon_j})}{var(\widetilde{DF}_j)}, \tag{18}$$

where $\widetilde{DF}$ and $\widetilde{\epsilon}$ are the residuals from a regression of DF and ϵ on X, respectively. If this is the case,

$$\hat{\lambda}_{2OLS} - \hat{\lambda}_{1OLS} \xrightarrow{p} \lambda_2 - \lambda_1 + (\frac{cov(\widetilde{DF}_2, \widetilde{\epsilon_2})}{var(\widetilde{DF}_2)} - \frac{cov(\widetilde{DF}_1, \widetilde{\epsilon_1})}{var(\widetilde{DF}_1)}). \tag{19}$$

Thus, the necessary and sufficient condition for the difference in coefficients to identify the effect of interest is that the covariance between the time-preference measure and the unobservables, after netting out other variables and scaling by the variance in the time-preference measure, is the same for the constrained and unconstrained groups.[12]

An empirical examination of Proposition 1 requires placing youths into "constrained" and "unconstrained" groups. Because directly observing which youths are constrained is not possible, I focus on correlates of ω (a youth's endowment) and $\bar{d}$ (a youth's borrowing limit) for making this determination. An increase in family resources (via ω) lowers optimal borrowing (d^*) in both states of the world and thus the likelihood that an individual is constrained at the borrowing limit, all else equal. Furthermore, the positive effect of β on the difference in utilities in the constrained case ($\partial D^{con}/\partial\beta$) is larger both when ω and $\bar{d}$

[11]Because differences in marginal effect estimates between "constrained" and "unconstrained" groups are very similar under both probit and linear probability models as shown later in the paper, I focus on identification under the linear probability model because the probit does not render a closed-form solution for the estimator of λ.

[12]The variance of the residuals of DF (after regressing on the control variables in the model) is extremely similar across race/ethnicity category and income tercile.

shrink. Thus, students who have more financial support and/or greater access to credit should experience a weaker relationship between time preferences and college decisions.[13]

As discussed in Section 1, I use family income (at age 17) and race as factors that are likely correlated with an individual's ability to finance consumption while in school. If youths from low-income and racial minority families have lower levels of wealth and/or less access to private credit than youths from high-income and white families, then time preference should have a stronger impact on college attendance for low-income and minority youths.[14] As shown in Equation (19), a problem arises if DF is differentially correlated with unobservables for blacks than it is for whites (or low-income youths than it is for high-income youths). In Section 4.2, I argue that several indirect checks on the plausibility of the identifying assumption strengthen its case: for example, when I examine how DF affects high-school completion (when credit constraints are unlikely to play a role) instead of college attendance, differences by race and family income largely disappear.

[13] I do not consider parental decisions about youth endowments (ω) in each state of the world. Weinberg (2001) considers a model in which wealthy parents can use financial incentives to induce good behavior (e.g. college enrollment) in children while poorer parents are limited in their ability to do so. If this is the case, wealthier parents may be able to induce "'low β" youths to attend college through the use of financial incentives that raise current consumption. Though the mechanism is different from my model, the underlying cause is the same–poor, impatient youths cannot move consumption into the present if they invest in their schooling, while wealthy, impatient youths can.

[14] Inasmuch as some black (low-income) youths are unconstrained and some white (high-income) youths are constrained, the difference in estimates of DF on college attendance for the two groups will understate the true difference between "constrained" and "unconstrained" youths. Thus, the estimates by race and income provide a lower bound on the difference by "constrained status" in this sense.

3 Data

3.1 Data description

I use the National Longitudinal Survey of Youth, 1979 cohort (NLSY79) throughout my empirical analysis. The NLSY79 is a nationally representative sample of youths who were between 14 and 22 years old in 1979. The survey was conducted annually until 1994, after which it has been conducted biennially. The disadvantage of using this data, then, is that it contains individuals who made college decisions in the 1980's rather than more recent cohorts. Though unfortunate, this is offset by several advantages: first, the NLSY79 includes a rarely asked question (in large, labor-oriented surveys) that aims to elicit individual time preferences and is the key variable in this study (this is discussed below). Second, it includes a very rich set of variables that are important controls in my analysis (including family background variables and academic test scores). Lastly, the NLSY79 has been used extensively in economics to not only examine higher education decisions in general, but the issue of educational credit constrains specifically. This allows me to easily compare my results with other studies on this question. I address this comparison and offer some clues on how my results might change for more recent cohorts in Sections 5 and 6.

Because I analyze the effect of patience on the decision to attend college, I need to control for a variety of individual and family characteristics (e.g. parental resources) at the time (or just prior to) youths are old enough for college. As a result, I include in my estimation sample only those youths for whom I have data prior to age 18 (those who were 14-17 years old in 1979).[15] 4,936 individuals fit into this category. Of these, 3,287 were still in the sample

[15]The total NLSY79 sample is composed of a random sample (representative of the non-institutionalized

at the time of the 2006 survey (which contains the measure of time preference used in this paper, as described below). 2,431 of these individuals do not have missing information on important explanatory variables (e.g. parental income at age 17). These 2,431 constitute the regression sample used throughout the paper.

The dependent variable used in my main analysis ("*attendcollege*") is a measure of college enrollment: it is a binary variable that takes a value of "1" if an individual completes at least 1 year of college and takes a value of "0" otherwise.[16] I focus on the discrete decision to attend college as a measure of schooling attainment because it represents the first educational investment with significant direct costs (e.g. tuition, room and board) for many youths. Since indirect (opportunity) costs do not need to be financed while one is in school (Cameron and Taber, 2004), borrowing constraints seem especially likely to bind for the college decision (if they bind at all). In a supplementary analysis, I examine the effect of individual discount rates on the probability of attaining other levels of education. Summary statistics by race/ethnicity and parental income status for educational attainment and all independent variables used throughout the paper are contained in Table 1.

The longitudinal nature of the NLSY79 is vital for this study, as it allows me to connect the college attendance decision typically made in young adulthood with a measure of time preferences elicited later in life (the key independent variable in my analysis). The time-preference measure used in this paper is derived from a 2006 survey question regarding a

civilian population), a minority (black and Hispanic) supplemental sample, a supplemental sample of economically disadvantaged youths, and a supplemental sample of youths in the military. This papers employs the random and minority samples but does not make use of the economically disadvantaged or military samples.

[16]The results in the paper are robust to modifying the dependent variable to reflect a more lax definition of college attendance: ever having been enrolled in at least one year of college. I choose to focus on the definition presented in the text to avoid calling youths who dropped out very shortly after enrolling in college (perhaps due to financial reasons) "college attenders."

hypothetical intertemporal trade-off. This question states:

> "Suppose you have won a prize of \$1,000, which you can claim immediately. However you have the alternative of waiting one year to claim the prize. If you do wait, you will receive more than \$1,000. What is the smallest amount of money in addition to the \$1,000 you would have to receive one year from now to convince you to wait rather than claim the prize now?"

I follow Courtemanche et al. (2014) in computing a respondent's discount factor ("*DF*") from their answer to this question (which I refer to as "*amount*") as follows:

$$DF = \frac{1,000}{1,000 + amount}. \quad (20)$$

[17]

Several issues related to using DF as a proxy for individual discount factors are fleshed out in the next subsection.[18] Means and standard deviations of DF by race/ethnicity and parental income tercile are displayed in Table 1. The average discount factor in the full sample is 0.54, which implies a discount rate of 85%.[19] Though this may appear high, other

[17] This formulation assumes that the \$1,000 is consumed instantly and in isolation from other sources of consumption. As noted in Courtemanche et al. (2014), it also assumes a linear utility function (utility may be approximately linear over this relatively small amount of money). To examine the effect of time preferences on educational attainment when these assumptions are relaxed, I also simply divide DF into quartiles and look at differences in (regression adjusted) means. This formulation only assumes that higher levels of DF correspond with more patient preferences. These results are contained in Tables 6 and 7.

[18] These issues are discussed in detail in Frederick, Loewenstein, and O'Donoghue (2002).

[19] A small number (238) of individuals in the sample report an answer of "0" as the extra amount they would require to wait 1 year to receive the prize (which implies a value of $DF = 1$). Though this value is not inconsistent with theory, the data suggests that many in this group were either incorrectly trying to skip the question or did not understand it. Comparing these individuals to those who are in the highest quartile of DF (those who answered the intertemporal trade-off question with small but positive values) suggest they are very different groups: the mean income level in 2006 of the $DF = 1$ group is roughly \$55,000, while that of those in the highest quartile of DF is approximately \$100,000. The $DF = 1$ group have observable characteristics that much more closely resemble those in the *lowest* DF quartile: for example, the mean income of that group is about \$58,000. Because the characteristics of the individuals in the $DF = 1$ group are so different from the characteristics of their peers, I drop them from the analysis. Alternatively, if these individuals are coded as the most impatient group ($DF = 0$), results in the paper change very little.

studies have documented discount rates of similar magnitudes when individuals are faced with real or hypothetical intertemporal trade-offs (Warner and Pleeter, 2001; Chesson et al., 2006). Consistent with Lawrance (1991), minority individuals and individuals who were poorer as youths indicate more impatience about the future (lower values of DF, on average), but differences in means across these categories are relatively small, and the variance of DF is very similar for different racial and income groups. The full histograms of DF by race/ethnicity and parental income tercile are displayed in Figures 1 and 2, respectively.

In addition to DF, explanatory variables used throughout the analysis include sex, race/ethnicity, presence of both biological parents in the home, urban residence, number of siblings, mother's education, Armed Forces Qualifying Test (AFQT) percentile, family income at age 17, and birth cohort. Summary statistics for each of these variables are contained in Table 1. These control variables are designed to account for family support for college (financial and otherwise) and a youth's academic ability, which in turn are related to the other independent variables in the theoretical model (one's endowment, earnings profile in each state of the world, and college costs).

AFQT score is an important control in this analysis as it is a widely accepted measure of cognitive achievement.[20] The AFQT represents a youth's performance on the word knowledge, paragraph comprehension, arithmetic reasoning, and numerical operations portions of a broader test called the Armed Services Vocational Aptitude Battery (ASVAB), which is normally used by the military. The test was administered to NLSY79 youths as part of the survey process.

[20]Neal and Johnson (1996, pg. 871) find that the AFQT is a "racially unbiased measure of basic skills that helps predict actual job performance." Lochner and Monge-Naranjo (2011, pg. 2490) state that AFQT scores are "strongly correlated with post-school earnings conditional on educational attainment."

In the NLSY79, youths are grouped into three mutually exclusive race/ethnicity categories: Hispanic, black, and non-Hispanic, non-black (the last of which I refer to as "white" youths for the sake of brevity). In Section 4.1, I analyze the effect of DF on college attendance for each of these three categories, and I do the same by family income tercile.

3.2 Using DF to approximate personal discount factors

This subsection addresses concerns related to the use of DF as a proxy for individual time preferences. The first of these is that the question is based on a hypothetical, rather than real, trade-off. However, several studies, including Johnson and Bickel (2002), Madden et al. (2003), and Locey, Jones, and Rachlin (2011) find no evidence that discounting over real rewards differs from discounting over hypothetical rewards in experimental settings. A second issue is twofold: first, this question was part of the 2006 survey (when respondents were all over 40 years old), well after college decisions had been made by NLSY79 respondents; in addition, time preferences may be endogenously determined in part by schooling experiences (Becker and Mulligan, 1997).

To examine whether my proxy for time preferences in middle adulthood is a good predictor of time preferences in late adolescence, I consider the relationship between DF and smoking behavior in 1984 (the first year in which smoking behavior is available in the NLSY79) since smoking has been demonstrated to be associated with impatience in other studies (e.g. Scharff and Viscusi, 2011). Youths in my sample were between ages 19 and 22 in 1984. Table 2 contains the results of a probit regression in which the dependent variable ("*dailysmoker*") takes a value of "1" if in 1984 the individual reported smoking 1 or more cigarettes per day over the last month (and is "0" otherwise). The left column of Table 2 contains the marginal effect of DF on *dailysmoker* from a regression with no other covariates, while the right column reports the same effect from a regression containing the right-hand side controls discussed in Section 3. Without the inclusion of other covariates, a 1 standard deviation (0.24) increase in the discount factor is associated with a 4 percentage point decline in the probability of daily smoking when young (a 12 percent difference at the mean of the dependent variable). When other controls (including family income at age 17, test scores, and mother's education) are included, this effect is reduced somewhat (to an 8 percent decline), but it remains both economically and statistically significant (at the 1 percent level).

Even though DF is correlated with smoking behavior as we would expect for a proxy for time preferences, it is at best a noisy measure of underlying preferences. A well-known result is that classical (white noise) measurement error leads coefficient estimates to be biased toward zero. If the degree of measurement error (and the variance of DF) were the same across race and family income, the difference in DF estimates for constrained and unconstrained groups would be attenuated in the same proportion. Such a situation would then bias away from finding a difference in the effect of DF on college enrollment by race and family income (the prediction of the model).[21]

The smoking results are suggestive of a positive correlation in individual discount rates

[21] It may also be the case that the correlation between DF and underlying time preferences varies by race or income. To investigate this possibility, I run similar regressions to those reported in Table 2 separately by race/ethnicity category and family income tercile. This reveals that the effect of DF on the probability of smoking is somewhat stronger for whites and high-income youths (though no differences are statistically significant at conventional levels). This would seem to suggest that, if anything, measurement error in DF for minorities and low-income youths is larger, which would again tend to bias against finding evidence in favor of the model's predictions. These results are available upon request.

throughout one's life, though they certainly do not rule out the possibility that unobserved factors drive the correlation between smoking, education, and DF, nor do they rule out the possibility that higher levels of education contribute to more patient preferences. However, as discussed in Section 1, I appeal to *differences* in the effect of DF on college enrollment by race/ethnicity and parental income for support of my hypothesis. Under the hypothesis that time preferences and educational attainment are related due to credit constraints, the correlation between DF and college attendance should systematically vary by wealth/access to credit (as proxied by race) and income; it is not clear why this should be the case if the correlation is merely spurious or due to reverse causality.

The last concern related to my measure of time preference (DF) is that it might reflect the marginal interest rate an individual faces rather than her intertemporal discount rate. Indeed, since NLSY79 respondents are in their 40's at the time they are asked the question, most (if not all) are unlikely to be credit constrained at that stage of their lives (more than 90% of the sample have positive net worth as of 2004).[22] Theoretically, then, most individuals should answer the question by giving the market interest rate. However, even a cursory glance at responses to the hypothetical intertemporal trade-off question suggests that this is not what individuals have in mind when answering the question. For example, among the highest net-worth tercile in 2004 (median net worth of $314,000), more than 87% (hypothetically) demand a return of more than 10% in order to postpone receiving the $1,000 prize for 1 year (versus 95% and 93% for those in the lowest and middle terciles, respectively). The full histograms of DF by 2004 net worth tercile are contained in Figure 3.

It appears that few if any respondent submit as their discount rate the interest rate they

[22] I use net worth information from 2004 because it is not collected in the 2006 survey.

would expect to receive if they were to invest \$1,000 today. The finding that imputed discount rates are much higher than market interest rates is common in the literature (see Frederick et al., 2002) and suggests individuals do take into account their personal time preferences when considering a hypothetical trade-off such as the one described above. However, it should be noted that other factors may be responsible for this phenomenon as well (e.g. the uncertainty associated with waiting to receive a prize).

4 Empirical results

4.1 Main results

The main results of the paper come from estimating Equations (15) and (16) as probit regressions.[23] Once again, I use race/ethnicity and family income categories to proxy for groups who are more or less likely to be borrowing constrained. In Tables 3 through 5, marginal effects and robust standard errors are reported from a probit regression of "*attendcollege*" on "DF" and the set of control variables described in Section 3.1. Table 3 contains the results for the full regression sample as well as for men and women individually. Table 4 shows the results of three separate regressions for whites, blacks, and Hispanics, respectively. Table 5 reports results from regressions run for each family income (at age 17) tercile separately.

The leftmost column of Table 3 shows that increasing DF from 0 to 1 increases the likelihood of college attendance by 12.3 percentage points. Thus, a 1 standard deviation increase in DF of 0.24 raises the likelihood of attendance by 3 percentage points (roughly a

[23]Linear probability specifications for the full sample and by race/ethnicity and income tercile are contained in Appendix Table 1. Marginal effects are similar to, though slightly smaller than, those presented in the body of the paper.

6 percent difference at the mean). The second and third columns of Table 3 show that the effect is very similar for men and women. The effects of other explanatory variables are as expected. Mothers education, AFQT score, and parental income contribute positively to the likelihood of college enrollment. Though the effect of income and its square are individually not statistically different from zero for the full sample, the hypothesis that they are jointly equal to zero is rejected at the 5 percent level. The marginal effect on the probability of college attendance of a \$10,000 (in \$2007) increase in family income at the mean is just over 1 percentage point. Raising AFQT score by 1 percentile also increases the probability of college by a little more than 1 percentage point. Females and minorities are more likely to attend college holding all else equal. However, these effects should be interpreted cautiously, because blacks and Hispanics tend to have much lower family incomes and AFQT scores than whites (which can lead to a problem of insufficient overlap when estimating partial effects; see, for example, Barsky et al., 2002).

Table 4 estimates separate models by race/ethnicity. As discussed in Section 1, I expect the effect of DF on college attendance to be strongest for blacks, because their families have lower levels of wealth than whites (even after conditioning on income) and may have less access to private credit markets as well (recall that the results in this paper do not control for family wealth because it is not included in the NLSY79). Thus, it should be harder for blacks to smooth consumption while in school than it is for whites, on average, resulting in a stronger relationship between time preference and college attendance for blacks than for whites.

The results in Table 4 are supportive of this hypothesis. While the effect of DF on college attendance is small and statistically insignificant for whites (a 1 standard deviation increase raises the probability of college by less than 1 percentage point among whites), it is economically large and statistically significant at the 1 percent level for blacks. An increase in DF of 1 standard deviation is associated with an increase in the probability of college by almost 6 percentage points among blacks, or almost 13 percent at the mean. The coefficients for blacks and whites are statistically different from each other at the 10 percent level. Interestingly, the coefficient on DF for Hispanics lies between the black and white extremes, though it is imprecisely estimated (note that the sample of Hispanics is the smallest of the three groups).

Table 5 shows a similar pattern in the effect of DF on the likelihood of college attendance by family income tercile. For those with the lowest family incomes (the first column), the probability of attendance increases by 4 percentage points (11 percent at the mean) when DF increases by 1 standard deviation. This effect is statistically significant at the 5 percent level and is more than three times as large as the point estimate for youths in the highest income tercile (though it should be noted that these coefficients are not statistically distinguishable at conventional levels). Those in the middle income tercile see a 2.5 percentage point increase in their college probability for every 1 standard deviation increase in DF, but the effect is not statistically significant.

Tables 6 and 7 show the results of regressions with quartiles of DF on the right-hand side (rather than DF in levels). The quartiles specification only assumes that higher levels of DF (corresponding with lower amounts required to wait 1 year to receive $1,000) are indicative of more patient preferences rather than the cardinal assumption underlying the interpretation of DF in Tables 3 through 5. The results are consistent with those reported in earlier specifications: in particular, blacks in the lowest DF quartile are 15 percentage points less likely to attend college than those in the highest quartile, while the difference in enrollment probabilities between the lowest and highest DF quartiles among the lowest family income tercile is almost 13 percentage points.[24] The corresponding figures for whites and high-income youths are roughly 2 and 4 percentage points, respectively.

The results discussed above show a stronger relationship between time preferences and college enrollment for minority and low-income students. However, so far I have not analyzed the effect of DF on the probability of college by race/ethnicity and income class simultaneously. These results are displayed in Table 8. This table shows marginal effects of DF from probit regressions for each race/ethnicity (white, black, or Hispanic) and income tercile combination separately. The large positive effect of DF on college attendance is especially concentrated among low-income blacks and Hispanics. Somewhat curiously, low-income whites experience no DF effect, similar to the experience of middle and high-income whites.

There are a few things to note about Table 8. First, given the small sample sizes associated with each race/income bin, results should be interpreted cautiously.[25] Second, to the extent that low-income whites are not susceptible to DF while others are, it may indicate that they generally have higher levels of family support or better access to formal credit markets than do minority students (this was the original reason for looking at the effect of DF by race/ethnicity in the first place). Another possibility is that whites are better informed of the availability of funding for higher education (and thus realize that college will not require as large a sacrifice, in terms of consumption, as what blacks/Hispanics be-

[24] The quartiles in each specification are based on cutoffs from the full sample and not each race/income group separately.

[25] For example, the large, negative effect of DF on high-income Hispanics is unexpected, but the sample size is very small, and this is the only instance of a statistically significant, negative DF effect in the paper.

lieve). Because in this case blacks and Hispanics would be acting *as if* they were credit constrained even though they may not be, I cannot rule out this possibility with the current set of results. However, even if this were the case, the large effect of time preferences on college behavior would indicate that an important factor influencing the college decisions of low-income minorities is the potential loss of consumption during school (apart from their ability to pay direct schooling costs).[26]

4.2 The Effect of DF on other measures of education

An important question in this study is whether DF, the measure of time preferences used in this paper, is correlated with unobserved factors that influence college decisions themselves. Key among potential unobservables is taste for schooling, since the model in Section 2 predicts that this variable alters the relationship between time preference and schooling. Other unobserved variables, such as cognitive ability, may also be correlated with DF and thus be responsible for at least part of the observed relationship between DF and college enrollment. In this section, I deal with these threats to identification in several ways. I first look at the relationship between DF and observable measures of schooling tastes and ability, commenting on what that implies for the potential relationship between DF and unobservables. I then examine how DF affects schooling at other points in the highest grade completed distribution in which youths are less susceptible to credit constraints.

I begin by examining a variable that is only contained in the first wave of the survey, 1979. Youths were asked to identify how satisfied they were with their current school (with the

[26] In results available upon request, I find that average tuition levels among public 2-year colleges in one's state are uncorrelated with DF for all racial/ethnic groups even though they are highly correlated with actual enrollment rates. This is some evidence that DF itself is not correlated with perceptions of the affordability of college.

possible answers being "very satisfied," "somewhat satisfied," "somewhat dissatisfied," and "very dissatisfied"). I create an indicator variable that is equal to one if the answer is "very satisfied" and zero otherwise. This variable serves as a proxy for schooling tastes during high school in this analysis. Appendix Table 2 shows that this variable is positively related to college attendance even after controlling for the same set of right-hand side variables used throughout the paper (the relationship is somewhat stronger and statistically significant for minority and lower-income students). However, this same measure of schooling tastes has very little correlation with DF for all samples used in the paper, as seen in Table 9. Thus, at least according to this measure of schooling preferences, there is little reason to believe that DF is simply masking the effect of tastes for schooling.

In order to gain insight into the relationship between schooling achievement and DF, I examine how DF relates to youths' AFQT percentile scores. The results of several OLS regressions to this effect appear in Table 10. DF is in fact strongly related to AFQT score in the sample as a whole: a 1 standard deviation increase in DF is associated with a 3.5 percentile point increase in AFQT percentile. This result may indicate that youths with higher discount factors are more likely to invest in their human capital while in high school, perhaps because they are more likely to sacrifice time and effort in the present for a future reward. AFQT score is a control variable in all specifications presented in this paper, but the worry is that other, uncontrolled factors related to a youth's ability are also correlated with DF.

In this paper, the question is whether the effect of unobservables is larger for minorities and/or low-income students given that DF has a substantially larger effect on college attendance for those groups. If AFQT score is correlated with such unobservables, the results in the rest of the table indicate the opposite is true, if anything–the correlation between DF and AFQT is generally strongest for whites and high-income students (percentage effects, shown in brackets below standard errors, are a bit more similar across race and income tercile than are point estimates). Thus, it appears that if racial or income differences in the correlation between unobserved ability and DF exist, they bias against the findings presented in Section 4.1.

Another question is whether race/ethnicity or income tercile are themselves correlated with schooling tastes. If, for example, white kids did not mind school while blacks generally disliked it, the results presented in Section 4.1 could be due to that fact rather than group differences in the likelihood of being credit constrained. This possibility seems unlikely given the results in Tables 3 and 9. In the latter table, blacks and Hispanics have a (marginally insignificant) higher likelihood of being satisfied with their school, while Table 3 indicates that college enrollment percentages are also higher for minorities, all else equal. It is difficult to reconcile these findings with the notion that whites are not affected by DF because they enjoy school while others do not.

I perform one final exercise aimed at determining whether the relationship between DF and college attendance is truly indicative of credit constraints. Up until now, I have only analyzed the college attendance decision, but Figures 4 and 5 show how DF affects the probability of completing at least x years of education, for all $x = 12, ..., 18$. Marginal effects (at the mean) are displayed along with associated 95 percent confidence intervals. Though it is theoretically possible that DF would affect high-school completion, it is unlikely that failing to finish high school would lead to large increases in consumption for most youths. Enrolling in college, with its associated increase in direct and indirect costs, has much greater potential to limit consumption (relative to not attending). Thus, we would expect the effect of DF to increase when going from at least 12 to at least 13 years of schooling. This also becomes a falsification test for the identification strategy in this paper: if DF is merely a proxy for schooling tastes or other unobservables, a sharp change in the DF effect from 12 to 13 years of education is less likely.

Figure 4 contains results by race/ethnicity. In the full sample, the effect of DF on the probability of getting 13 or more years of education is about 10 percentage points higher than that of getting 12 or more years. This is largely driven by the experience of blacks and, to a lesser extent, Hispanics. Unfortunately, differences between the effect of DF at these two points of the education distribution are not statistically significant in any case, but they are economically large (the difference for blacks is almost 20 percentage points). After 13 years of schooling, the DF effect weakens, perhaps indicating that time preferences play their most important role in the decision of whether or not to even attend college (as opposed to whether to continue in college, conditional on initial enrollment). Figure 5 paints a similar picture with respect to income class–marginal effects of DF are larger at 13 years of schooling than at 12 years of schooling for all income classes, with the change being slightly larger for low and middle-income youths.

Overall, the results presented in this section are consistent with the hypothesis that credit constraints play a significant role in young people's educational decisions through the channel of limited consumption smoothing. Among whites and youths in the highest income tercile (who themselves have college attendance rates of substantially less than 100 percent), the correlation between time preferences and college enrollment is very weak. This is a striking result, given that it is plausible that discount rates as measured in the NLSY79 are correlated with factors that affect schooling but are not observed in this study (and for that reason alone may be correlated with college enrollment). Rather, by contrasting those findings with the result that time preferences have a large effect on the college choices of blacks and low-income youths, it seems likely that borrowing constraints are driving the overall relationship between patience and schooling.

5 Discussion

An estimate of the number of youths who are credit constrained due to an inability to smooth consumption can be obtained by comparing college enrollment rates among more patient (high DF) and less patient (low DF) individuals. I follow the technique in Carneiro and Heckman (2002) by multiplying the percentage of youths in each of the lower three quartiles of DF by their respective (regression-adjusted) deficit in college enrollment compared with the top quartile (this then assumes that youths in the upper quartile of DF are not constrained due to consumption concerns). Using this method, I find that roughly 6.5 percent of blacks and 8 percent of Hispanics are constrained. When the analysis is done by income tercile, alternatively, I find that 5.5 percent of youths in the lowest quartile and 4.5 percent of youths in the middle quartle are constrained.

These figures imply that overall roughly 3 percent of youths do not attend college due to an inability to smooth consumption.[27] This appears small, but there are several reasons

[27] Carneiro and Heckman (2002) assume that youths in the top family income quartile are not credit constrained and compare their college outcomes with those in lower quartiles. Also using the NLSY79, they find that roughly 4 percent of youths are constrained with respect to the enrollment decision. My results suggest that the largest enrollment gaps among lower-income youths are for those youths with impatient preferences (low DF), strengthening the idea that low-income youths are indeed less likely to enroll in college because of borrowing constraints (in particular, the inability to smooth consumption) as opposed to some other reason.

why it should be taken as a conservative estimate of the current role of credit constraints in youths' higher education decisions. First, this analysis isolates the impact of consumption smoothing concerns (by focusing on enrollment gaps between more and less patient youths, conditional on other characteristics) apart from the role that an inability to pay the *direct* costs of college plays in college decisions. Second, constraints on borrowing for college have become binding for more youths over time. This paper uses the younger cohorts of the NLSY79 who made college entrance decisions in the early 1980's. Belley and Lochner (2007) and Lochner and Monge-Naranjo (2011) point out that since the 1980's, college costs and returns have increased–as has the role of family income in young adults' schooling decisions–while government student loan limits have changed little. Lochner and Monge-Naranjo (2011) report that the proportion of students taking the maximum federal Stafford student loan amount tripled over the 1990's to 52 percent.

While private loans have increased over this time period to fill the gap, disbursement of these loans is based on the probability of repayment, raising the possibility that youths from disadvantaged backgrounds are in a relatively worse position than they were 30 years ago. Though government loans have never supported "non-schooling" consumption, the fact that many student now hit absolute financial aid limits to pay larger and larger tuition costs suggests that for youths with little family support, an inability to smooth consumption during college is at least as much of a concern as it has been in the past.

6 Conclusion

This paper proposes a novel way to examine whether credit constraints hinder human capital development among young people. An inability to borrow against future earnings prevents full consumption smoothing while an individual is in school. I hypothesize that this inability will be especially costly to youths who place more emphasis on current consumption relative to future consumption. Using a measure of individual time preferences collected in the NLSY79, I show that individuals who discount the future more heavily are less likely to attend college conditional on a rich set of individual and family characteristics. I then investigate whether this relationship differs systematically by race/ethnicity and family income, given that individuals from families of lower means will likely have the hardest time replacing consumption during their college years. This distinction has the added advantage of addressing endogeneity concerns, since under alternative explanations for why discount rates are related to schooling (omitted variables, reverse causality), it is not immediately clear why there should be an effect for blacks but not whites and for low-income youths but not high-income youths.

My results indicate that time discount rates play a meaningful role in the college choices of youths who are likely to have fewer financial resources while they are in school (minorities and youths with low family income) but little role in the decisions of whites and high-income youths. They also shed new light on the relationship between family income and schooling. Studies using the NLSY79 have typically found a fairly small effect of family income on college going for youths in this cohort once other factors such as aptitude (as measured by AFQT scores) are accounted for (see, for example, Carneiro and Heckman, 2002). This study shows that financial resources do not affect the college decisions of all youths equally. Rather, because government and institutional aid covers direct schooling costs but does not fully offset the indirect costs of attending college, family aid matters especially to those youths for whom lean consumption during college is distasteful (i.e. those with high discount rates). Whether expanding financial aid to allow more consumption smoothing during college would be welfare enhancing depends on many factors, including how many youths would increase their educational investments with more generous funding and what the return on those extra investments would be. This is a topic for future study.

A Appendix

Proof that $\frac{\partial D^{con}}{\partial \beta} - \frac{\partial D^{unc}}{\partial \beta} > 0$:

I wish to examine if:

$$\frac{\partial(\frac{(\omega+\bar{d}-\tau)^{\gamma}}{\gamma} + \beta\frac{(y_{1,2}-R\bar{d})^{\gamma}}{\gamma} - \frac{z_0^{\gamma}}{\gamma}(1+\beta^{\frac{1}{1-\gamma}}R^{\frac{\gamma}{1-\gamma}})^{1-\gamma})}{\partial\beta} > \frac{\partial((\frac{z_1^{\gamma}}{\gamma} - \frac{z_0^{\gamma}}{\gamma})(1+\beta^{\frac{1}{1-\gamma}}R^{\frac{\gamma}{1-\gamma}})^{1-\gamma})}{\partial\beta}. \quad (21)$$

Taking the derivative of both sides and cancelling common terms yields:

$$\frac{(y_{1,2}-R\bar{d})^{\gamma}}{\gamma} > \frac{z_1^{\gamma}}{\gamma}\frac{(\beta R)^{\frac{\gamma}{1-\gamma}}}{(1+\beta^{\frac{1}{1-\gamma}}R^{\frac{\gamma}{1-\gamma}})^{\gamma}} \quad (22)$$

This inequality holds as long as:

$$\bar{d} < \frac{y_{1,2}}{R} - z_1\frac{\beta^{\frac{1}{1-\gamma}}R^{\frac{\gamma}{1-\gamma}}}{1+\beta^{\frac{1}{1-\gamma}}R^{\frac{\gamma}{1-\gamma}}}. \quad (23)$$

The right-hand side of this inequality is simply the optimal debt holding d^* when an individual is unconstrained, so the condition holds whenever $\bar{d}$ is a relevant restriction.

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Figure 1: Histograms of Discount Factor (DF) by race/ethnicity category

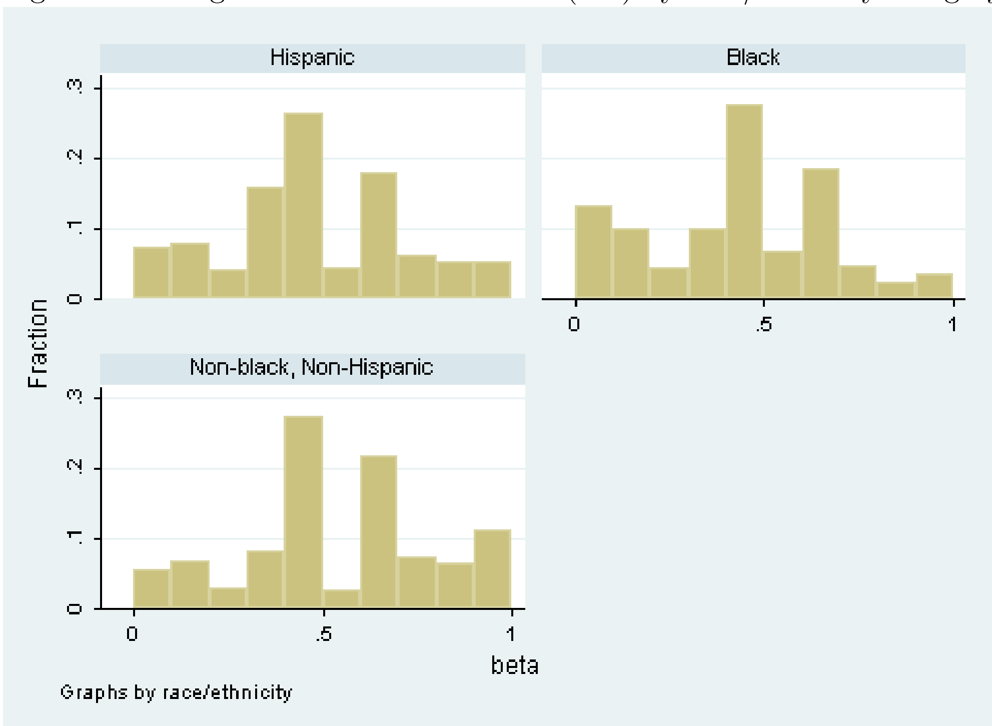

Figure 2: Histograms of Discount Factor (DF) by family income tercile (at age 17)

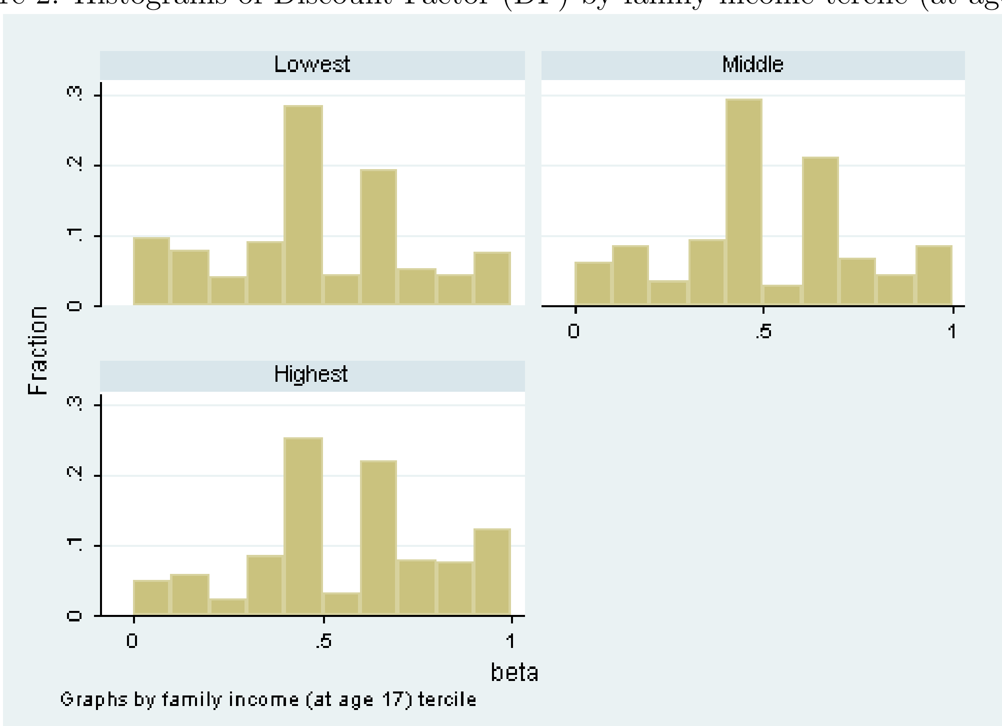

Figure 3: Histograms of Discount Factor (DF) by 2004 net worth tercile

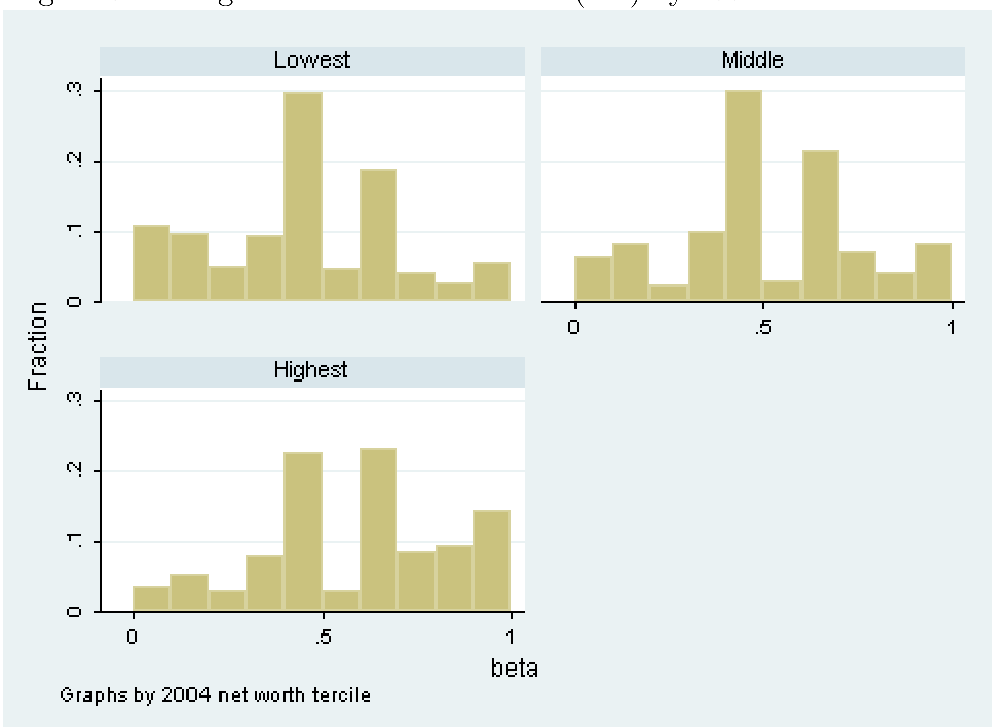

Figure 4: The Effect of DF on the probability of completing various years of schooling, by race/ethnicity

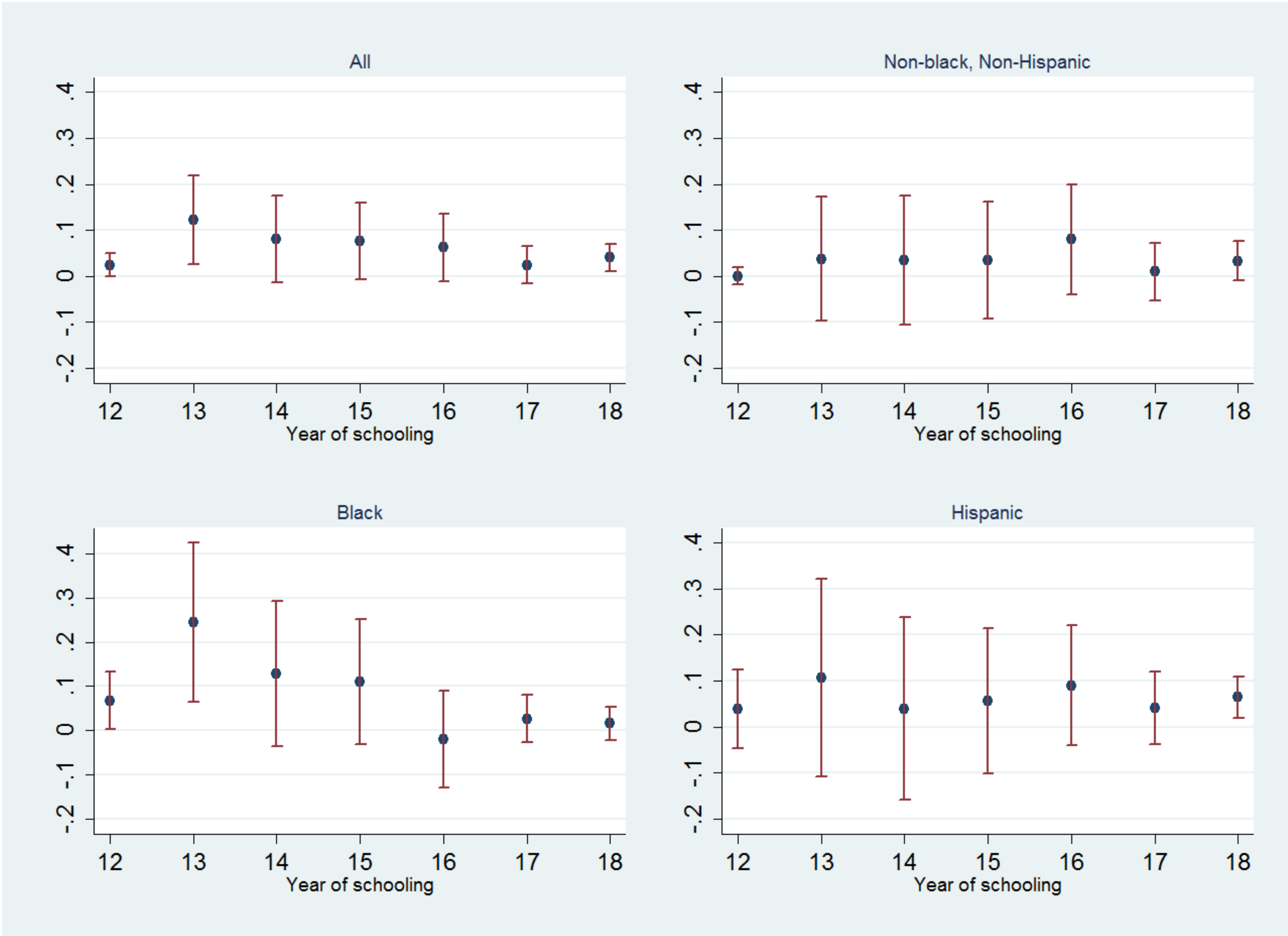

Figure 5: The Effect of DF on the probability of completing various years of schooling, by family income tercile

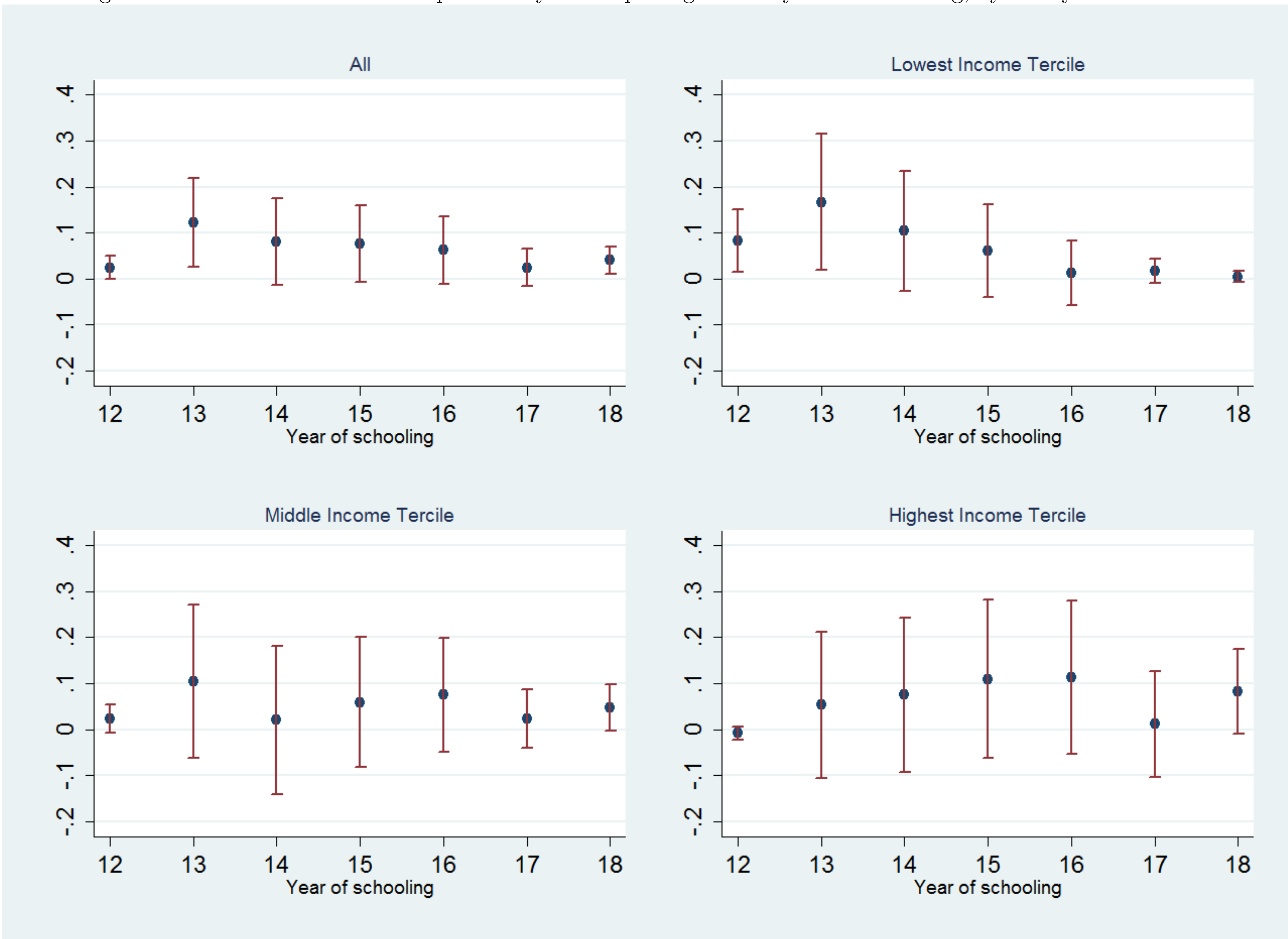

Table 1: Summary statistics for regression samples (NLSY79)

	By race/ethnicity			By family income tercile (at age 17)		
	Non-black, non-Hispanic (n=1,286)	Black (n=681)	Hispanic (n=464)	Lowest tercile (n=831)	Middle tercile (n=793)	Highest tercile (n=807)
	Mean (Std. dev.)	Mean (Std. dev.)	Mean (Std. dev.)	Mean (Std. dev.)	Mean (Std. dev.)	Mean (Std. dev.)
Attended college	0.54	0.47	0.42	0.37	0.47	0.65
	(0.50)	(0.50)	(0.49)	(0.48)	(0.50)	(0.48)
Highest grade completed	13.94	13.26	13.05	12.88	13.43	14.60
	(2.56)	(2.20)	(2.43)	(2.27)	(2.40)	(2.52)
Discount factor (computed from amount needed to wait 1 year to receive $1,000)	0.56	0.45	0.50	0.50	0.53	0.58
	(0.24)	(0.24)	(0.23)	(0.24)	(0.24)	(0.24)
Female	0.48	0.50	0.48	0.47	0.50	0.47
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Black	---	---	---	0.29	0.12	0.04
	---	---	---	(0.45)	(0.32)	(0.20)
Hispanic	---	---	---	0.11	0.06	0.03
	---	---	---	(0.32)	(0.23)	(0.18)
Non-black, non-Hispanic	---	---	---	0.60	0.83	0.93
	---	---	---	(0.49)	(0.38)	(0.26)
At least 1 biological parent not in home during adolescence	0.21	0.52	0.32	0.46	0.29	0.12
	(0.41)	(0.50)	(0.47)	(0.50)	(0.45)	(0.32)
Urban residence at age 17	0.73	0.83	0.92	0.71	0.71	0.81
	(0.44)	(0.38)	(0.27)	(0.45)	(0.45)	(0.39)
Number of siblings	2.86	4.29	4.12	3.86	3.07	2.73
	(1.90)	(2.84)	(2.78)	(2.68)	(2.10)	(1.76)
Mother less than a high-school diploma	0.26	0.50	0.69	0.56	0.33	0.17
	(0.44)	(0.50)	(0.46)	(0.50)	(0.47)	(0.38)
Mother high-school graduate	0.51	0.36	0.20	0.33	0.51	0.52
	(0.50)	(0.48)	(0.40)	(0.47)	(0.50)	(0.50)
Mother some college or more	0.23	0.14	0.10	0.11	0.16	0.31
	(0.42)	(0.34)	(0.30)	(0.31)	(0.37)	(0.46)
AFQT percentile	51.28	22.40	30.68	31.54	45.13	55.60
	(26.61)	(19.06)	(22.81)	(26.17)	(26.14)	(25.57)
Parental income at age 17 (in $10,000's)	6.45	3.50	4.33	1.77	4.60	9.27
	(3.74)	(2.78)	(3.06)	(0.82)	(0.85)	(3.11)
Age 17 in 1979	0.27	0.28	0.27	0.29	0.26	0.27
	(0.44)	(0.45)	(0.44)	(0.45)	(0.44)	(0.44)
Age 17 in 1980	0.27	0.29	0.27	0.24	0.30	0.27
	(0.44)	(0.45)	(0.44)	(0.42)	(0.46)	(0.44)
Age 17 in 1981	0.28	0.27	0.26	0.27	0.27	0.28
	(0.45)	(0.44)	(0.44)	(0.45)	(0.45)	(0.45)
Age 17 in 1982	0.19	0.17	0.21	0.21	0.17	0.19
	(0.39)	(0.38)	(0.41)	(0.40)	(0.37)	(0.39)

Notes: Observations are weighted using 2006 NLSY sampling weights. There are 2,431 total observations. Dollar amounts are denominated in $2007.

Table 2: Probit estimates of the effect of Discount Factor on daily smoking at ages 19-22

	Dependent variable: smokes at least 1 cigarette daily	
	Without additional covariates	With additional covariates
Discount factor	-0.165***	-0.108***
	(0.039)	(0.041)
Female	---	-0.006
	---	(0.019)
Black	---	-0.129***
	---	(0.025)
Hispanic	---	-0.176***
	---	(0.024)
Urban residence at age 17	---	-0.006
	---	(0.024)
Number of siblings	---	0.005
	---	(0.004)
Mother high-school graduate	---	-0.028
	---	(0.024)
Mother some college or more	---	-0.016
	---	(0.033)
AFQT percentile	---	-0.002
	---	(0.001)
AFQT percentile (in 10's) squared	---	-0.002
	---	(0.002)
Parental income at age 17 (in $10,000's)	---	-0.006
	---	(0.008)
Parental income at age 17 (in $100,000's) squared	---	0.024
	---	(0.047)
Observations	2,409	2,409

Notes: *** p<0.01, ** p<0.05, * p<0.1. Point estimates are from separate Probit regressions (1 for each column) and represent marginal effects at the mean of all independent variables in the model. Robust standard errors are in parentheses. Year effects are not reported.

Table 3: Probit estimates of the effect of Discount Factor on college attendance

	Dependent variable: completed at least 1 year of college		
	Full sample	Men	Women
Discount factor	0.123**	0.115	0.121*
	(0.049)	(0.071)	(0.067)
Female	0.120***	---	---
	(0.023)	---	---
Black	0.347***	0.316***	0.379***
	(0.030)	(0.046)	(0.037)
Hispanic	0.214***	0.158***	0.262***
	(0.034)	(0.051)	(0.043)
Urban residence at age 17	0.017	-0.026	0.057
	(0.028)	(0.041)	(0.039)
Number of siblings	-0.017***	-0.024***	-0.009
	(0.005)	(0.008)	(0.007)
Mother high-school graduate	0.101***	0.089**	0.112***
	(0.028)	(0.040)	(0.037)
Mother some college or more	0.307***	0.233***	0.375***
	(0.033)	(0.053)	(0.037)
AFQT percentile	0.016***	0.014***	0.018***
	(0.002)	(0.002)	(0.002)
AFQT percentile (in 10's) squared	-0.006***	-0.003	-0.009***
	(0.002)	(0.002)	(0.002)
Parental income at age 17 (in $10,000's)	0.007	0.008	0.007
	(0.010)	(0.014)	(0.014)
Parental income at age 17 (in $100,000's) squared	0.019	0.005	0.038
	(0.058)	(0.080)	(0.087)
Observations	2,431	1,211	1,220

Notes: *** p<0.01, ** p<0.05, * p<0.1. Point estimates are from separate Probit regressions (1 for each column) and represent marginal effects at the mean of all independent variables in the model. Robust standard errors are in parentheses. Year effects are not reported.

Table 4: Probit estimates of the effect of Discount Factor on college attendance by race/ethnicity

	Dependent variable: completed at least 1 year of college		
	Non-black, non-Hispanic	Black	Hispanic
Discount factor	0.037	0.245***	0.107
	(0.069)	(0.092)	(0.110)
Female	0.067**	0.157***	0.171***
	(0.032)	(0.043)	(0.050)
Urban residence at age 17	0.005	-0.036	0.139*
	(0.037)	(0.054)	(0.079)
Number of siblings	-0.014*	-0.019**	-0.013
	(0.009)	(0.008)	(0.010)
Mother high-school graduate	0.122***	0.158***	-0.005
	(0.040)	(0.048)	(0.068)
Mother some college or more	0.344***	0.273***	0.262***
	(0.040)	(0.071)	(0.099)
AFQT percentile	0.012***	0.026***	0.021***
	(0.003)	(0.003)	(0.004)
AFQT percentile (in 10's) squared	-0.002	-0.020***	-0.015***
	(0.003)	(0.004)	(0.004)
Parental income at age 17 (in $10,000's)	0.007	0.009	0.030
	(0.014)	(0.019)	(0.023)
Parental income at age 17 (in $100,000's) squared	0.035	0.036	-0.202
	(0.077)	(0.126)	(0.147)
Observations	1,286	681	464

Notes: *** p<0.01, ** p<0.05, * p<0.1. Point estimates are from separate Probit regressions (1 for each column) and represent marginal effects at the mean of all independent variables in the model. Robust standard errors are in parentheses. Year effects are not reported.

Table 5: Probit estimates of the effect of Discount Factor on college attendance by family income tercile

	Dependent variable: completed at least 1 year of college		
	Lowest family income tercile	Middle family income tercile	Highest family income tercile
Discount factor	0.167**	0.105	0.053
	(0.076)	(0.085)	(0.081)
Female	0.142***	0.070*	0.133***
	(0.036)	(0.040)	(0.037)
Black	0.278***	0.384***	0.229***
	(0.051)	(0.045)	(0.042)
Hispanic	0.155**	0.277***	0.114**
	(0.063)	(0.055)	(0.052)
Urban residence at age 17	0.020	-0.018	0.056
	(0.044)	(0.047)	(0.050)
Number of siblings	-0.021***	-0.014	-0.009
	(0.007)	(0.010)	(0.010)
Mother high-school graduate	0.131***	0.060	0.131***
	(0.044)	(0.046)	(0.050)
Mother some college or more	0.184**	0.328***	0.320***
	(0.081)	(0.056)	(0.044)
AFQT percentile	0.018***	0.016***	0.011***
	(0.003)	(0.003)	(0.003)
AFQT percentile (in 10's) squared	-0.011***	-0.006**	-0.002
	(0.003)	(0.003)	(0.003)
Parental income at age 17 (in $10,000's)	0.066	0.169	0.006
	(0.089)	(0.264)	(0.032)
Parental income at age 17 (in $100,000's) squared	-0.873	-1.939	0.011
	(2.654)	(2.893)	(0.133)
Observations	831	793	807

Notes: *** p<0.01, ** p<0.05, * p<0.1. Point estimates are from separate Probit regressions (1 for each column) and represent marginal effects at the mean of all independent variables in the model. Robust standard errors are in parentheses. Year effects are not reported.

Table 6: Probit estimates of the effect of Discount Factor quartiles on college attendance by race/ethnicity

	Dependent variable: completed at least 1 year of college		
	Non-black, non-Hispanic	Black	Hispanic
2nd quartile of Discount factor	-0.015	0.143***	0.039
	(0.045)	(0.054)	(0.064)
3rd quartile of Discount factor	0.065	0.108*	-0.035
	(0.047)	(0.055)	(0.071)
4th quartile of Discount factor	0.018	0.150*	0.106
	(0.048)	(0.077)	(0.081)
Female	0.066**	0.154***	0.177***
	(0.032)	(0.043)	(0.051)
Urban residence at age 17	0.009	-0.035	0.140*
	(0.037)	(0.054)	(0.080)
Number of siblings	-0.015*	-0.018**	-0.013
	(0.009)	(0.008)	(0.010)
Mother high-school graduate	0.121***	0.159***	-0.014
	(0.040)	(0.048)	(0.068)
Mother some college or more	0.341***	0.273***	0.253**
	(0.041)	(0.071)	(0.101)
AFQT percentile	0.012***	0.026***	0.021***
	(0.003)	(0.003)	(0.004)
AFQT percentile (in 10's) squared	-0.002	-0.020***	-0.016***
	(0.003)	(0.004)	(0.005)
Parental income at age 17 (in $10,000's)	0.006	0.011	0.032
	(0.014)	(0.019)	(0.023)
Parental income at age 17 (in $100,000's) squared	0.037	0.025	-0.215
	(0.077)	(0.126)	(0.147)
Observations	1,286	681	464

Notes: *** p<0.01, ** p<0.05, * p<0.1. Point estimates are from separate Probit regressions (1 for each column) and represent marginal effects at the mean of all independent variables in the model. Robust standard errors are in parentheses. Year effects are not reported. The omitted Discount factor quartile is the 1st (lowest, or least patient) quartile.

Table 7: Probit estimates of the effect of Discount Factor quartiles on college attendance by family income tercile

	Dependent variable: completed at least 1 year of college		
	Lowest family income tercile	Middle family income tercile	Highest family income tercile
2nd quartile of Discount factor	0.072	-0.002	0.058
	(0.047)	(0.052)	(0.050)
3rd quartile of Discount factor	0.092*	0.044	0.036
	(0.052)	(0.054)	(0.054)
4th quartile of Discount factor	0.127**	0.068	0.041
	(0.063)	(0.062)	(0.054)
Female	0.140***	0.067*	0.131***
	(0.036)	(0.040)	(0.037)
Black	0.277***	0.381***	0.230***
	(0.051)	(0.045)	(0.042)
Hispanic	0.154**	0.275***	0.112**
	(0.063)	(0.055)	(0.053)
Urban residence at age 17	0.021	-0.016	0.055
	(0.044)	(0.047)	(0.049)
Number of siblings	-0.022***	-0.014	-0.008
	(0.007)	(0.010)	(0.010)
Mother high-school graduate	0.132***	0.059	0.130***
	(0.044)	(0.046)	(0.050)
Mother some college or more	0.186**	0.329***	0.321***
	(0.081)	(0.056)	(0.044)
AFQT percentile	0.018***	0.016***	0.011***
	(0.003)	(0.003)	(0.003)
AFQT percentile (in 10's) squared	-0.011***	-0.006**	-0.002
	(0.003)	(0.003)	(0.003)
Parental income at age 17 (in $10,000's)	0.062	0.167	0.007
	(0.090)	(0.264)	(0.032)
Parental income at age 17 (in $100,000's) squared	-0.761	-1.918	0.009
	(2.660)	(2.892)	(0.134)
Observations	831	793	807

Notes: *** p<0.01, ** p<0.05, * p<0.1. Point estimates are from separate Probit regressions (1 for each column) and represent marginal effects at the mean of all independent variables in the model. Robust standard errors are in parentheses. Year effects are not reported. The omitted Discount factor quartile is the 1st (lowest, or least patient) quartile.

Table 8: Probit estimates of the effect of Discount Factor on college attendance by race/ethnicity and family income tercile

	Dependent variable: completed at least 1 year of college		
	Non-black, non-Hispanic	Black	Hispanic
Lowest family income tercile	-0.048	0.251**	0.317**
	(0.149)	(0.117)	(0.144)
	[229]	[386]	[216]
Middle family income tercile	0.038	0.174	0.045
	(0.116)	(0.176)	(0.189)
	[438]	[208]	[147]
Highest family income tercile	0.058	0.163	-0.629**
	(0.092)	(0.197)	(0.309)
	[619]	[87]	[101]

Notes: *** p<0.01, ** p<0.05, * p<0.1. Point estimates are from separate Probit regressions (1 for each income tercile, race/ethnicity pair) and represent the marginal effect of DF on the probability of college attendance at the mean of all independent variables in the model for various subgroups. Robust standard errors are in parentheses. Number of observations are in brackets. Coefficients on other right-hand side variables are not reported.

Table 9: Probit estimates of the effect of Discount Factor on taste for schooling

	Dependent variable: very satisfied with his/her school in 1979						
	Full sample	Non-black, non-Hispanic	Black	Hispanic	Lowest family income tercile	Middle family income tercile	Highest family income tercile
Discount factor	-0.013	-0.028	-0.019	0.015	0.002	-0.009	-0.018
	(0.045)	(0.062)	(0.083)	(0.108)	(0.078)	(0.080)	(0.077)
Female	0.016	0.030	-0.039	0.071	0.015	0.003	0.039
	(0.021)	(0.029)	(0.040)	(0.050)	(0.037)	(0.037)	(0.036)
Black	0.047	---	---	---	0.090*	0.044	0.027
	(0.030)	---	---	---	(0.052)	(0.051)	(0.064)
Hispanic	0.043	---	---	---	0.112*	-0.022	0.090
	(0.032)	---	---	---	(0.060)	(0.053)	(0.059)
Urban residence at age 17	-0.012	-0.033	-0.002	0.129	-0.018	-0.036	0.012
	(0.026)	(0.033)	(0.049)	(0.082)	(0.045)	(0.043)	(0.048)
Number of siblings	-0.010**	-0.004	-0.015**	-0.012	-0.019***	-0.001	-0.009
	(0.005)	(0.008)	(0.007)	(0.010)	(0.007)	(0.009)	(0.010)
Mother high-school graduate	0.026	0.100***	-0.055	-0.037	0.022	0.005	0.059
	(0.026)	(0.037)	(0.045)	(0.067)	(0.045)	(0.043)	(0.052)
Mother some college or more	-0.003	0.050	-0.047	-0.001	-0.039	-0.048	0.041
	(0.035)	(0.047)	(0.068)	(0.097)	(0.074)	(0.061)	(0.058)
AFQT percentile	-0.002	0.001	-0.004	-0.007*	-0.007***	0.002	0.002
	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
AFQT percentile (in 10's) squared	0.004***	0.001	0.007	0.010**	0.011***	0.001	0.001
	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Parental income at age 17 (in $10,000's)	-0.012	-0.010	-0.013	-0.022	0.023	0.373	0.010
	(0.009)	(0.012)	(0.019)	(0.023)	(0.094)	(0.249)	(0.031)
Parental income at age 17 (in $100,000's) squared	0.017	-0.006	0.050	0.127	-1.255	-4.209	-0.073
	(0.050)	(0.064)	(0.135)	(0.148)	(2.818)	(2.729)	(0.130)
Observations	2,259	1,207	632	420	744	737	778

Notes: *** p<0.01, ** p<0.05, * p<0.1. Point estimates are from separate Probit regressions (1 for each column) and represent marginal effects at the mean of all independent variables in the model. Robust standard errors are in parentheses. Year effects are not reported.

Table 10: OLS estimates of the effect of Discount Factor on AFQT percentile

	Dependent variable: AFQT percentile score						
	Full sample	Non-black, non-Hispanic	Black	Hispanic	Lowest family income tercile	Middle family income tercile	Highest family income tercile
Discount factor	14.740***	19.128***	3.603	15.890***	6.064**	15.365***	20.991***
	(1.858)	(2.793)	(2.957)	(4.112)	(2.911)	(3.379)	(3.427)
	[0.38]	[0.38]	[0.16]	[0.53]	[0.24]	[0.39]	[0.40]
Female	0.495	1.322	0.062	-1.287	1.696	-1.102	0.692
	(0.864)	(1.302)	(1.366)	(1.847)	(1.383)	(1.588)	(1.563)
Black	-18.237***	---	---	---	-16.234***	-20.208***	-17.630***
	(1.136)	---	---	---	(2.023)	(1.859)	(2.387)
Hispanic	-11.160***	---	---	---	-10.411***	-10.673***	-11.924***
	(1.274)	---	---	---	(2.271)	(2.226)	(2.293)
Urban residence at age 17	2.116**	3.975***	0.047	-0.523	0.399	4.831**	1.108
	(1.071)	(1.465)	(1.554)	(3.300)	(1.659)	(1.875)	(2.092)
Number of siblings	-1.075***	-1.542***	-0.728***	-1.184***	-0.757***	-1.439***	-1.156***
	(0.178)	(0.342)	(0.252)	(0.356)	(0.232)	(0.345)	(0.428)
Mother high-school graduate	8.810***	11.279***	5.116***	9.075***	7.816***	8.164***	11.198***
	(1.067)	(1.649)	(1.496)	(2.645)	(1.759)	(1.752)	(2.113)
Mother some college or more	18.061***	20.397***	12.374***	18.781***	18.173***	18.259***	19.081***
	(1.506)	(2.071)	(2.674)	(4.269)	(3.510)	(2.620)	(2.428)
Parental income at age 17 (in $10,000's)	1.993***	2.104***	1.106*	3.046***	-1.246	-2.566	2.558**
	(0.355)	(0.526)	(0.658)	(0.684)	(3.330)	(10.488)	(1.290)
Parental income at age 17 (in $100,000's) squared	-5.622***	-6.581**	1.442	-15.313***	162.435	40.949	-8.011
	(2.015)	(2.728)	(5.266)	(3.725)	(102.391)	(115.777)	(5.212)
Observations	2,431	1,286	681	464	831	793	807
R-squared	0.396	0.242	0.170	0.243	0.267	0.306	0.307

Notes: *** p<0.01, ** p<0.05, * p<0.1. Point estimates are from separate OLS regressions (1 for each column) and represent marginal effects. Robust standard errors are in parentheses. Percentage effects at the mean for each group are in brackets. Year effects are not reported.

Appendix Table 1: Linear probability estimates of the effect of Discount Factor on college attendance

	Dependent variable: completed at least 1 year of college						
	Full sample	Non-black, non-Hispanic	Black	Hispanic	Lowest family income tercile	Middle family income tercile	Highest family income tercile
Discount factor	0.089**	0.018	0.193***	0.084	0.133**	0.077	0.034
	(0.037)	(0.051)	(0.068)	(0.090)	(0.063)	(0.068)	(0.064)
Female	0.088***	0.044*	0.120***	0.136***	0.113***	0.060*	0.100***
	(0.017)	(0.023)	(0.033)	(0.042)	(0.030)	(0.031)	(0.029)
Black	0.273***	---	---	---	0.222***	0.313***	0.244***
	(0.024)	---	---	---	(0.040)	(0.038)	(0.052)
Hispanic	0.165***	---	---	---	0.121***	0.226***	0.100**
	(0.027)	---	---	---	(0.046)	(0.047)	(0.050)
Urban residence at age 17	0.011	0.000	-0.023	0.113	0.016	-0.016	0.033
	(0.022)	(0.027)	(0.041)	(0.074)	(0.036)	(0.038)	(0.039)
Number of siblings	-0.012***	-0.009	-0.015**	-0.010	-0.016***	-0.012	-0.007
	(0.004)	(0.006)	(0.006)	(0.008)	(0.005)	(0.008)	(0.008)
Mother high-school graduate	0.085***	0.101***	0.123***	0.006	0.110***	0.051	0.121***
	(0.023)	(0.032)	(0.040)	(0.060)	(0.037)	(0.038)	(0.045)
Mother some college or more	0.244***	0.276***	0.222***	0.211***	0.152**	0.268***	0.283***
	(0.029)	(0.039)	(0.058)	(0.079)	(0.067)	(0.050)	(0.050)
AFQT percentile	0.013***	0.010***	0.021***	0.017***	0.015***	0.013***	0.012***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
AFQT percentile (in 10's) squared	-0.005***	-0.002	-0.017***	-0.011***	-0.008***	-0.004**	-0.004**
	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Parental income at age 17 (in $10,000's)	0.008	0.008	0.011	0.024	0.049	0.131	0.007
	(0.007)	(0.009)	(0.014)	(0.018)	(0.069)	(0.209)	(0.022)
Parental income at age 17 (in $100,000's) squared	-0.007	-0.003	-0.018	-0.166	-0.544	-1.498	-0.011
	(0.036)	(0.043)	(0.080)	(0.114)	(2.107)	(2.292)	(0.088)
Observations	2,431	1,286	681	464	831	793	807
R-squared	0.292	0.330	0.294	0.230	0.250	0.250	0.305

Notes: *** p<0.01, ** p<0.05, * p<0.1. Point estimates are from separate OLS regressions (1 for each column) and represent marginal effects. Robust standard errors are in parentheses. Year effects are not reported.

Appendix Table 2: Probit estimates of the effect of taste for schooling on college attendance

	Dependent variable: completed at least 1 year of college						
	Full sample	Non-black, non-Hispanic	Black	Hispanic	Lowest family income tercile	Middle family income tercile	Highest family income tercile
Very satisfied with his/her school in 1979	0.057**	0.049	0.087*	0.057	0.080**	0.074*	0.018
	(0.024)	(0.033)	(0.046)	(0.054)	(0.040)	(0.041)	(0.038)
Observations	2,259	1,207	632	420	744	737	778

Notes: *** p<0.01, ** p<0.05, * p<0.1. Point estimates are from separate Probit regressions (1 for each column) and represent marginal effects at the mean of all independent variables in the model. Robust standard errors are in parentheses. Coefficients on other right-hand side variables are not reported.