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MONEY OR GRIT? DETERMINANTS OF MISMATCH BY RACE AND GENDER

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Abstract

This paper studies mismatch in educational attainment. Mismatch arises when high ability individuals do not obtain a college degree and/or low ability individuals do obtain such a degree. Using data from the NLSY97 survey, the paper estimates a structural model of education choice that matches the moments of mismatch, college attainment and labor market outcomes. The analysis conditions on both gender and race. The model with occasionally binding borrowing constraint fits the moments better than a model with perfect capital markets, indicating that capital market frictions may contribute to mismatch. The influence of parents on educational attainment is present though this channel appears to operate through attitudes rather than through the provision of resources. Once this link between parents and children is taken into account, the influence of borrowing constraints disappears. In this case, mismatch reflects differences in tastes rather than borrowing constraints. The paper also presents a decomposition of the college wage premium into the returns to schooling and the selection into higher education. The analysis highlights the power of selection into higher education as an explanation of the college wage premium by gender and race.

JEL classification: I26, J24

1 Introduction

This paper studies mismatch in the allocation of individuals to educational attainment. This is a topic of considerable interest as it is central to the debate on both the efficiency and equity of the educational system. Mismatch is often viewed as a signal of misallocation in the assignment of individuals to education outcomes.

Mismatch in educational attainment can arise in essentially two forms. In the case of an under-match, a relatively high ability individual does not go to college. Under-match is frequently associated with imperfect capital markets so that high ability individuals with limited resources find a college education too expensive. Alternatively, it might be that the individual is simply not motivated nor otherwise equipped for the rigors of college life. These competing explanations are summarized as "money" or "grit", though as we shall see, the non-financial factors that influence the education choice may go well beyond determination alone.

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In the alternative case of over-match, a relatively low ability individual obtains a college degree. This is not the consequence of capital market imperfections. But, as in the case of under-match, tastes might matter in the form of motivation and grit strong enough to compel a low ability individual through college.

This paper is about the magnitudes and determinants of mismatch. Bowen and Bok (1998) for the first time brought public attention to the significance of mismatch. Their book discussed the issue of mismatch from the perspective of long-term consequences of using affirmative action and provided evidence that minority students do as well as or better than their white counterparts at the nation's top universities on a number of educational outcomes. The authors use twenty-eight private and public colleges and universities taken from the College and Beyond database as the nation's top higher education institutions, including all the ivy league institutions. Although critiqued by the non-representativeness of the sample, their study has far-reaching effects on later research on mismatch.

There are now numerous studies of mismatch using US data. Our measures of mismatch follow the approach of Smith, Pender, and Howell (2013), adding a structural interpretation of their measures. Dillon and Smith (2013) study mismatch based on the National Longitudinal Survey of Youth from 1997 (hereafter NLSY97). They find evidence of both under- and over-match. Their analysis includes a measure of college quality so that mismatch also refers to the relationship between the ability of a student and the quality of college the student attends.

Our approach and findings differ from the extant literature as we formulate a dynamic choice problem and use that structure to estimate key parameters. The estimation follows a simulated method of moments approach, where the mismatch rates are prominent features of the data that we match. Apart from the differences in methodology, unlike these earlier studies, we look at college attainment instead of college participation. This is important because both the gender gap and racial gap in college participation have shrunk in the past decades whereas the gap in college attainment still largely remains.

The model allows for three sources of mismatch. First, borrowing constraints can create an under-match. Second, variations across individuals in tastes for education can create both under- and over-match. Finally, the test score observed in the data, as described below, may itself be a noisy measure of ability. This model explains "observed" mismatch simply as measurement error.[1]

The estimation uses moments from the NLSY97. In addition to the measured under- and over-match rates, we use moments associated with the individual's education choice as a function of their (ASVAB) test score as well as their labor market outcomes, also as a function of their test score. The moments are calculated, and thus the estimation is undertaken, for the whole sample as well as sub-groups distinguished by gender and race.

This data set figures prominently in the literature on mismatch and more generally in the discussion of borrowing constraints, as in Lochner and Monge-Naranjo (2011). As discussed in Belley and Lochner (2007a), capital market imperfections appear more prominent in the NLSY97 data compared to the NLSY79 data, as studied by Cameron and Heckman (2001) and Keane and Wolpin (2001). We return to this debate both through our analysis of the role of borrowing constraints and more generally the impact of family resources and background on educational attainment and mismatch.

Our baseline model distinguishes the three sources of mismatch in a setting without explicit parental influence. There are two initial findings regarding model features that match the data moments. First, there is evidence of

[1] Cooper and Liu (2016) undertakes a similar exercise looking at college attainment across countries. They argue that mismatch is primarily a consequence of mis-measured ability through noisy test scores.

capital market frictions for the full sample as well as the groups distinguished by gender and race. Second, taste shocks (grit) are important source of mismatch, noisy test scores are not.

It is natural to study the influence of the families in generating these results. One might conjecture that the estimated borrowing constraint provides a channel through which family resources can influence education choice. But, as emphasized in Cameron and Heckman (2001), family income may be highly correlated with other dimensions of family life that impact educational decisions through tastes rather than a budget constraint.

We expand our analysis to allow either family income or mother's education to influence the education choice. The specification in which the mother's education proxies for taste shocks fits the moments very closely. A specification which links mother's education to the child's ability produces a close fit as well. This is the case even if there are no borrowing constraints.

As in Cameron and Heckman (2001), it seems that family influence through tastes and/or ability is more powerful than simply shifting a budget constraint. In these model with an active role for parent's education, mismatch arises largely from taste shocks as there is no evidence of binding borrowing constraints. Noise in the test score also creates the appearance of mismatch.

The estimated model provides a neat decomposition of the college wage premium. The return to education is estimated and the selection into college is determined by the choice problem of individual agents. Looking, for example, at the black and white sub-groups, the college wage premium in the simulated data is about 50% higher for blacks despite the fact that the return to education is about 50% that of the whites. The wage premium is driven solely by selection. Conditional on attaining college, the average ability of a black individual is more than thrice that of a white.

2 Evidence of MisMatch

This section presents our data and evidence of mismatch. The moments presented here are subsequently used in the structural estimation.

2.1 Data

The data are drawn from the 1997 National Longitudinal Survey of Youth (NLSY97).[2] The data include individuals born between 1980 and 1984. At the time of first interview in 1997, respondents' ages ranged from 12 to 18. The respondents were 28 to 34 at the time of their round 16 interviews in 2013. Most respondents graduated high school and made their college choice between 1999 and 2002. Our main analysis is about mismatch between measured ability and educational attainment.

ASVAB is the measure of ability. Most NLSY97 respondents participated in the administration of the computer-adaptive form of the Armed Services Vocational Aptitude Battery (CAT-ASVAB) in 1997. The ASVAB test has 12 components, a subset of which including mathematical knowledge (MK), arithmetic reasoning (AR), word knowledge (WK), and paragraph comprehension (PC) is referred to as Armed Forces Qualification Test (AFQT). It has been demonstrated in the literature that AFQT is a good measure of ability and is statistically significant in predicting

[2]For details, see `https://www.nlsinfo.org/content/cohorts/nlsy97`. Education attainment and wages are taken from the 2012 wave and the ASVAB exam score is reported in the 1997 wave.

outcomes (see Cawley, Conneely, Heckman, and Vytlacil (1997) and Cawley, Heckman, and Vytlacil (2001)). Our analysis is based on categorizing individuals according to their AFQT score quartiles.

Given that the main component of our analysis is a measure of cognitive ability, we only focus on individuals whose ASVAB score quartiles are non-negative. This yields a sample of 6,599 individuals for the analysis.

We use a dichotomous variable to measure educational attainment - whether an individual has at least obtained a bachelors degree or not in 2013, the latest round of interview. We do not count those who have only obtained AA degrees as having college attainment.

For some of the analysis, we condition on race/ethnicity. The analysis mainly focuses on two ethnic group: blacks and whites (defined as non-black and non-hispanic).

2.2 Mismatch

We construct a measure of mismatch following Smith, Pender, and Howell (2013). Consider a logistic regression to characterize education choice at the individual level:

$$Pr(e_i = 1) = \frac{exp^{\alpha_0+\alpha_1 a_i}}{1 + exp^{\alpha_0+\alpha_1 a_i}} \tag{1}$$

where a_i is the ASVAB test score of individual i. Here $e_i = 0$ signifies that an individual has no college degree and $e_i = 1$ signifies college attainment and beyond. As the analysis proceeds additional covariates will be added to this basic regression.

This regression generates the coefficients (α_0, α_1). At this stage, these are treated as moments from the data, with the interpretation coming through the structural estimation.

The under- and over-match rates come from this regression. A household is under-matched if it does not have a college degree but, through (1), the probability $e_i = 1$ exceeds the 80th percentile of all predicted values. Likewise, a household is over-matched if it has attained a college degree but the predicted probability that $e_i = 0$ is less than the 20th percentile of all predicted values.

Clearly the 20% and 80% percentiles are arbitrary, mismatch measures can be calculated with other cut-off values as well. Despite this, these measures are informative. These same cut-offs are used in the structural estimation so that actual and simulated data are treated in a similar way.

2.3 Moments

The set of data moments for the baseline models is presented in Table 1. The first column indicates the college attainment rate, ranging from 40.2% for female to 20.3% for blacks. The under- and over-match rates also vary substantially across the groups. The under-match rate is highest for blacks, at 12.2%. For all groups, the under-match rate exceeds the over-match rate. This is an important feature of the data that the estimated model will have to match.

The regression coefficients from (1), α_0 and α_1, are included as moments. This provides an informative link between the test score and the educational choice.

So entire sample size is 3241 male 1647 female 1594 white 1924 black 723

Table 1: Data Moments

	college	under-match	over-match	α_0	α_1	ν_1	ν_2	Obs.
all	0.346	0.094	0.020	-3.225	0.045	0.007	0.004	3241
				0.079	0.001	0.001	0.001	
male	0.294	0.095	0.013	-3.709	0.048	0.005	0.003	1647
				0.126	0.002	0.001	0.001	
female	0.402	0.092	0.028	-2.873	0.043	0.009	0.006	1594
				0.104	0.002	0.001	0.001	
white	0.397	0.082	0.040	-3.349	0.047	0.007	0.004	1924
				0.120	0.002	0.001	0.001	
black	0.203	0.122	0.016	-3.255	0.049	0.008	0.005	723
				0.146	0.003	0.001	0.001	

This table reports data moments from the NLSY97. "College" is the college rate. The regression coefficients α_0 and α_1 are from (1). The predicted values from this regression are used to create the under-match and over-match rates. The regression coefficients ν_1 and ν_2 are from (2) and (3) and characterize the response of wages to test scores. The last column indicates sample size.

A final piece of evidence used in the analysis is the dependence of compensation on the test score. This moment is important to discipline the noise of the test score in predicting ability. We regressed the log of the real hourly wage on the test score, with and without including an educational attainment dummy as a covariate. Specifically, letting i be an individual, the coefficients, ν_1 and ν_2 on the test score in Table 1 came from the following two regressions:

$$E[\omega_i|\cdot] = \nu_{01} + \nu_1 * test_i \tag{2}$$

and

$$E[\omega_i|\cdot] = \nu_{02} + \nu_2 * test_i + \nu_3 * ed_i \tag{3}$$

Including this mapping from test score and education to wages as moments implies that our model will, through the education decision based upon ability, indirectly create a college wage premium, a theme we return to in Section 7.

3 Model

This section outlines our model of household choice, drawing on the presentation in Cooper and Liu (2016). The focus of the model is on the education choice and the influence of tastes, capital markets and information on that decision. The model is then used as a basis for the estimation.

The model is simplified to highlight the education decision. In particular, there is no uncertainty over income or periods of unemployment. Further, the household does not have a complicated portfolio decision. As studied, for example in Cooper and Zhu (2015), households who differ by educational attainment also differ in terms of asset market participation, portfolio composition and portfolio adjustment patterns. While of interest, none of the dimensions of household finance seemed crucial to the educational attainment decision.

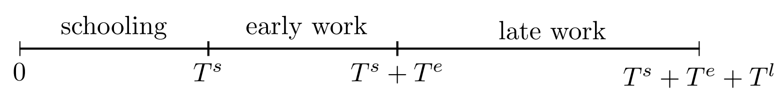
The households are of different "types". The heterogeneity is along multiple dimensions including: (i) cognitive ability, (ii) taste for education and (iii) initial wealth. These factors all contribute to the education decision.

3.1 LifeCycle

To study education choice and mismatch we consider a simple life-cycle model of the household. The model is complex enough to capture the costs and benefits of the college choice, abstracting from other choices on the allocation of time between study and work as well as the decision to complete college.

There are three phases as illustrated in Figure 1. During the first T^s periods of life, the individual can attend school and/or work. The second and third phases, of length T^e and T^l, are both periods of work with compensation reflecting two features: the education decision made in the first phase and the role of experience. The role of experience interacts with the education decision. In this way, the education choice influences both the level of lifetime compensation and its pattern over time. Let $T = T^s + T^e + T^l$ be the total lifetime of the household.

Figure 1: Phases of Lifecycle



This figure shows the household's lifecycle.

3.2 Perfect Capital Markets

The household compares the utility flow from a college degree with the utility without college attainment. Initially assume that the household is able to borrow and lend in perfectly competitive capital markets at an interest factor of R. In this setting, the household essentially ranks these options by comparing lifetime income, net of education costs. The only complicating factor is the presence of taste shocks in this choice.

For the analysis, let $e \in \{0, \bar{e}\}$ denote the education choice. Further, let θ denote the ability of the individual. Throughout we assume that θ is known to the agent.

The lifetime discounted present value of income for the individual is the sum of the discounted values from the three periods:

$$Y(e,\theta) = Y^s(e) + \frac{Y^e(e,\theta)}{R^{T^s}} + \frac{Y^l(e,\theta)}{R^{T^s+T^e}}, \tag{4}$$

for $e \in \{0, \bar{e}\}$. Throughout this discussion, define $\tilde{R}^x = \frac{R^{x-1}}{(1+R+R^2+...+R^{x-1})}$ where R is the real interest rate and x is the length of the period of the flow that is being discounted.

The income flow during the school phase is given by:

$$Y^s(e) = \frac{\omega_1(1-e) - p(e)}{\tilde{R}^{T^s}}. \tag{5}$$

This expression allows both the income and the tuition paid in the education phase to depend on the choice of e.

The return to education depends on the agent's ability through labor earnings in the second and third phases of the lifecycle. Specifically, a household of ability θ that chooses education $\bar{e}$ obtains labor income of $\omega_j H(\theta)$ for $j = 1$ (early work) and $j = 2$ (late work). In this specification, there is a complementarity between ability and the return to college. If instead the agent chooses no college, $e = 0$, then labor income is ω_j in period $j = 1, 2$, where $H(0,\theta) = 1$ for all θ.

The discounted present value of income over the early work phase of life is:

$$Y^e(e,\theta) = \frac{\omega_1 H(e,\theta)}{\tilde{R}^{T^e}} \tag{6}$$

for $e \in \{0, \bar{e}\}$ where $\tilde{R}^{T^e}$ discounts the flow of income during the middle phase back to the start of the early work period. Similarly, the discounted present value of income over the late work phase of life is:

$$Y^l(e,\theta) = \frac{\omega_2 H(e,\theta)}{\tilde{R}^{T^l}} \tag{7}$$

for $e \in \{0, \bar{e}\}$ where $\tilde{R}^{T^l}$ discounts the flow of income during the final phase back to the start of the late work period. Both of these flows depend on ability, θ, only if the agent attends college. Assume $\omega_2 \geq \omega_1$ to allow for some experience effect on wages which, as noted above, interacts with education.

3.2.1 No College

If the agent does not go to school, the discounted present value of net income during the school years is given by:

$$Y^s(0,\theta) = \frac{\omega_1}{\tilde{R}^{T^s}}. \tag{8}$$

In this case there is no tuition charge and the individual works full time, earning a base wage of ω_1. Note that the agent's ability θ does not factor into earnings during this period.

Further,

$$Y^e(0,\theta) = \frac{\omega_1}{\tilde{R}^{T^e}} \qquad \text{and} \qquad Y^l(0,\theta) = \frac{\omega_2}{\tilde{R}^{T^l}}. \tag{9}$$

Substituting these flows into (4) yields the discounted present value of income for the no college choice.

The household chooses consumption in each period of life, c_t, to maximize the discounted present value of lifetime utility subject to (4).

$$V^n = max_{c(t)} \sum_t \beta^t u(c(t)) \tag{10}$$

subject to:

$$\sum_t \frac{c(t)}{\tilde{R}^t} \leq Y(0,\theta). \tag{11}$$

where β is the household's discount rate and $u(\cdot)$ is strictly increasing and strictly concave. Assume $R\beta = 1$ so that the household has an incentive to completely smooth consumption.

Let V^n denote the solution of (10). To be clear, this value is independent of the ability of the agent.

3.2.2 College

If the agent goes to school, then the discounted present value of net income for the school phase becomes:

$$Y^s(\bar{e}, \theta) = \frac{\omega_1(1 - \bar{e}) - p}{\tilde{R}^{T^s}} \tag{12}$$

with $p = p(\bar{e})$. Here the agent works $(1 - \bar{e})$ units of time when not in school and pays tuition p. Again, ability does not enter into income during the education phase. Instead, ability is reflected in the return to education.

The incomes during the two working phases are given by:

$$Y^e(\bar{e}, \theta) = \frac{\omega_1 H(\bar{e}, \theta)}{\tilde{R}^{T^e}} \quad \text{and} \quad Y^l(\bar{e}, \theta) = \frac{\omega_2 H(\bar{e}, \theta)}{\tilde{R}^{T^l}}. \tag{13}$$

Substituting these flows into (4) yields the discounted present value of lifetime income if college is chosen.

Let $\tilde{V}^c(\theta)$ denote the value, dependent on ability, obtained by maximizing lifetime utility subject to a lifetime budget constraint given by $Y(\bar{e}, \theta)$ from (4). The value of college is also influenced by a taste shock, denoted by ε.

The taste shocks can reflect differences in parental attitudes about education and/or peer group pressure. They can also reflect determination and grit at the individual level.

$$V^c(\theta) = \tilde{V}^c(\theta) + \varepsilon. \tag{14}$$

3.2.3 Optimal Choice

As there are no capital market imperfections, then the household choice of education is simply a comparison of V^n and $V^c(\theta)$. Since lifetime income is an increasing function of ability, there will exist a critical value of ability, denoted θ^* such that $V^n = V^c(\theta^*)$. For this ability and above, college is the optimal choice of the household.

It is certainly possible for a high (low) ability agent to choose no college (college) because of a high (low) draw of the taste shock. Since, for example, the empirical model in (1) includes only a test score, taste shocks would be a source of measured mismatch.

But whether or not this mismatch is inefficient is an open issue. After all, the socially efficient allocation would allow the education choice to depend on tastes. But, if these tastes themselves came from some form of inefficient allocation of individuals to communities and/or peer groups, then the allocation could then be considered inefficient. The paper is agnostic about the inefficiency of mismatch due to taste shocks.

3.3 Borrowing Constraints

The borrowing constraint we consider limits the amount of debt an agent can accumulate to finance education expenses during the schooling phase.[3] Though this constraint does not arise directly from an incentive compatibility condition, the borrowing limit is estimated so that the frequency the constraint binds is a result rather than assumed.

Suppose an agent enters the early work period with B of debt outstanding. The value of income over the early and late working years discounted back to the start of the early work period is given by

[3]For the other phases of the lifecycle, the household is able to perfectly smooth consumption.

$$Y^{el}(\bar{e},\theta,B) = Y^e(\bar{e},\theta) + \frac{Y^l(\bar{e},\theta)}{R^{T^e}} - B \tag{15}$$

with $Y^e(\bar{e},\theta)$ and $Y^l(\bar{e},\theta)$ defined above. Since there are no further borrowing constraints, the household will smooth consumption over the early and late working periods given this level of income.

Given the absence of borrowing constraints after the first phase, the household will smooth consumption over the last two phases of life generating a flow of utility captured by the value $V^{el}(e,\theta,B)$ given by

$$V^{el}(e,\theta,B) = u(c^{el}(e,\theta,B))\tilde{\beta}^{(T^e+T^l)} \tag{16}$$

where $\frac{c^{el}(e,\theta,B)}{\tilde{R}^{T^{el}}} = Y^{el}(e,\theta,B)$.[4]

During the school years, suppose the household is unconstrained and has no outside wealth. The household will borrow b each period and consumes $c^s = \omega(1-\bar{e}) - p\bar{e} + b$. At the end of the school period, their debt outstanding is $B = b(1 + R + R^2 + ...R^{T^s-1})$.

Let $\bar{B}$ be a ceiling on debt outstanding at the end of the school period. When the constraint binds, i.e. $B > \bar{B}$, the household will continue to smooth consumption during the school phase but it is not able to smooth consumption between the school and working phases. Thus household consumption during each period of the school phase is given by

$$\frac{c^s(\bar{e},\theta,\bar{B})}{\tilde{R}^{T^s}} = \frac{\omega_1(1-\bar{e})}{\tilde{R}^{T^s}} - p\bar{e} + \bar{B}. \tag{17}$$

Using (16) as well as the consumption level given by (17), a household that chooses to go to college with a binding borrowing constraint has lifetime utility of $V^c(\theta,\bar{B}) = \tilde{\beta}^{T^s}u(c^s(\bar{e},\theta,\bar{B})) + \beta^{T^s}V^{el}(e,\theta,B)$. The household will choose to go to college iff $V^c(\theta,\bar{B}) + \varepsilon \geq V^n$. Clearly if the borrowing constraint binds the value of obtaining a college degree is lower, i.e. $V(\bar{e},\theta) > V(\bar{e},\theta,\bar{B})$.

The analysis ignores outside wealth of the agent. Yet for many students transfers from family members relax borrowing constraints. This can be included in the analysis as an additional source of wealth, denoted Z, in (17).[5] This transfer from parents could be individual specific, depending on a number of factors such as: (i) parental wealth, (ii) ability of their child and (iii) tastes for higher education.[6] Clearly a large enough Z offsets the effects of a binding borrowing constraint. This will be discussed further in the context of the estimation of a model that includes parental income and/or wealth.

The borrowing constraint can lead to an under-match. Some high ability individuals will choose not to attend college simply because the borrowing constraint limits their ability to smooth consumption and thus reduces the value of education. This will be more costly for small $\bar{B}$ and this will be part of the estimation.

[4]Here, $\tilde{R}^{T^{el}}$ and $\tilde{\beta}^{T^e+T^l}$ are defined following the notation developed.

[5]The constraint becomes

$$\frac{c^s(\bar{e},\theta,\bar{B})}{\tilde{R}^{T^s}} = \frac{\omega_1(1-\bar{e})}{\tilde{R}^{T^s}} - p\bar{e} + \bar{B} + Z.$$

.

[6]These interactions are introduced in the model in Section 6.

4 Estimation

This section outlines the estimation approach and the functional forms. It provides a bridge from the theory model to the results presented in the next section.

4.1 Functional Forms and Calibration

As in Cooper and Liu (2016), there are some functional form assumptions used in the empirical analysis. The ability distribution is assumed to be Pareto with a parameter of ϕ.[7] Taste shocks are assumed to be uniformly distributed around zero, i.e. $\varepsilon \in [-\bar{\varepsilon}, \bar{\varepsilon}]$. The parameters $(\phi, \bar{\varepsilon})$ are estimated. Period utility is represented by $u(c) = ln(c)$. The discount factor, $\beta = \frac{1}{R}$ with $R = 1.025$. Section 5.5 relaxes some of these assumptions and studies robustness of our findings.

The analysis uses the ASVAB test score in the estimation of (1) from data. In the model, a test score is simulated from the agents' ability according to:

$$ts_i = \theta_i + \sigma\zeta_i. \tag{18}$$

Here ζ_i is noise in the mapping between ability and the test score of agent i.[8] The parameter σ controls the amount of noise and is estimated. The rank of an agent's test score, ts_i, is used in the structural estimation, parallel to the data analysis.

This noise becomes another source of mismatch. But unlike a binding borrowing constraint or a taste shock, this mismatch reflects an underlying measurement problem. In the Cooper and Liu (2016) cross-country study, this was a major source of (measured) mismatch.

The human capital accumulation equation is given by $H(\bar{e}, \theta) = h(\bar{e})\theta$. The return to education, $h(\bar{e})$, is estimated by gender and race.

There are a number of variables calibrated for the analysis. From Table B1 in Johnson (2013), the cost of going to school, relative to labor income in the school phase, is $\frac{p}{\omega_1} = 0.25$. From the labor market outcomes reported in Table 2 of Johnson (2013), the time spent in school is given by $\bar{e} = 0.5$. The total cost of going to college is $0.75 * \omega_1$. The robustness section considers other values for these costs. Both tuition and the opportunity cost of education are assumed constant across gender and race.

The wage rate in the initial period is normalized: $\omega_1 = 1$. The wage rate for the late work period, ω_2, is set at 1.148. This is taken from estimates of the wage profile for the US in Hanushek, Schwerdt, Wiederhold, and Woessmann (2015).[9]

For the estimation, these variables are assumed not to vary by gender and race. Instead, the parameters do vary by gender and race to make the moments for each group.

[7] Specifically, the CDF of ability, θ, is given by $1 - \theta^{-\phi}$ with a mean of $\frac{\phi}{\phi-1}$.

[8] The noise is normally distributed with a zero mean.

[9] As a cross-check, lifecycle income profiles were estimated by education group for the PSID and the return for the two age groups was calculated from those estimates. Thanks to Guozhong Zhu for this evidence.

4.2 Approach

The estimation is through simulated method of moments. The parameter vector $\Theta = (\phi, \bar{\varepsilon}, \sigma, h(\bar{e}), \bar{b})$ is chosen to minimize the distance between simulated and data moments.

Formally, the estimation solves

$$min_{\Theta} \frac{(M^d - M^s(\Theta))}{M^d} W \frac{(M^d - M^s(\Theta))}{M^d}', \tag{19}$$

where W is the identity matrix. Here M^d are data moments and $M^s(\Theta)$ are moments calculated from simulated data. The procedure solves the household choice problem given the parameter vector Θ. Given these choices, a large data set (100,000 individuals) is simulated. The moments in $M^s(\Theta)$ are calculated, with one exception, from the simulated data in exactly the same manner as the data moments.[10]

The distance metric is the percentage difference between simulated and data moments. There is no weighting matrix used in the analysis.[11] Adda and Cooper (2003), and references therein, discusses this estimation approach.

The moments used for the estimation are given in Table 1. Thus we match the college rate, the logistic regressions characterizing individual educational attainment, the under- and over-match rates and the dependence of wages on test scores. These moments and thus the parameter estimates are studied for the entire sample as well as by gender and race.

5 Results

This section reports initial findings in which there are three sources of mismatch: (i) borrowing constraints, (ii) taste (grit) shocks and (iii) mismeasurement due to noisy test scores. The inference is based upon the initial model in which family characteristics and income are absent. The extensions of the model in Section 6 includes the influence of parents on children explicitly.

The parameter estimates are reported in Table 2 and the moments in Table 3. The rows correspond to a particular group in the sample. We first report and discuss results under the assumption of perfect capital markets and then turn to the estimation with borrowing constraints.

5.1 Perfect Capital Markets

The natural starting point is the model without borrowing constraints. In the two tables, the block labeled 'No BC' are the estimates and moments for the case of perfect capital markets.

From Table 2, the parameter of the Pareto distribution varies across the groups, with the value for males far exceeding that of females. Recall that the mean of the ability distribution is decreasing in ϕ. The estimated dispersion of taste shocks, $\bar{\varepsilon}$ is "large" while the amount of noise in the test score is essentially zero. This pattern is present for

[10]The exception has to do with the treatment of the test score. In the NLSY97 data, the normalized rank of the test score is reported, where the normalized score is over the entire sample. For computational ease, the ranking is within group in the simulated data. Using simulated data from the baseline model, the overall rank was calculated and the correlation of the within rank and overall rank was 0.98. The estimation matches a moment based upon this rank.

[11]We explore the robustness of our findings to an alternative objective function in Section 5.5.

all groups. The return to college, $h(\bar{e})$ varies across groups with the blacks having the lowest return and males the highest return.

Table 2: Parameter Estimates

	ϕ	$\bar{\varepsilon}$	σ	$h(\bar{e})$	$\bar{b}$
		No BC			
all	2.318	16.871	0.019	0.567	na
male	3.594	10.757	0.000	0.740	na
female	1.928	19.788	0.004	0.515	na
white	2.844	13.191	0.004	0.704	na
black	1.676	24.940	0.001	0.381	na
		BC Baseline			
all	2.610	12.435	0.010	0.690	0.775
male	3.593	8.644	0.002	0.810	0.796
female	2.173	16.393	0.000	0.688	0.371
white	3.040	11.088	0.009	0.903	0.231
black	1.595	24.951	0.006	0.442	0.044
		Estimated No Taste Shocks: $\bar{\varepsilon} == 0$			
all	2.136	0	0.878	0.755	0.611
male	3.445	0	0.351	0.834	0.938
female	1.678	0	1.401	0.662	0.772
white	2.227	0	0.873	0.836	0.693
black	1.480	0	2.170	0.463	0.555
		Estimated No Test Noise: $\sigma == 0$			
all	2.607	12.486	0	0.689	0.790
male	3.593	8.644	0	0.810	0.796
female	2.171	16.394	0	0.687	0.370
white	3.040	11.088	0	0.903	0.231
black	1.595	24.947	0	0.442	0.044

This table reports parameter estimates for the baseline model without and with borrowing constraints, no taste shocks and the no test noise cases.

The moments in Table 3 are useful for understanding these differences in parameter estimates. As noted earlier, there are a couple of leading differences across the groups: (i) the education rate for blacks is lower and for females higher than the pooled sample, (ii) the under-match rate exceeds the over-match rate for all groups and this is amplified for blacks. The other moments are very similar across the groups including the logistic coefficients and the dependence of wages on test scores. The challenge for the estimation is to use a relatively small number of parameters to match these features of the data.

While the estimated model does generate some dispersion in college rates by gender and race, the differences are not nearly as large as in the data. These differences in college rates correspond to estimated differences in the ability distribution. For example, the higher college rate for females follows from the lower estimate of ϕ and thus higher average ability for that group. Likewise, males have the highest estimated value of ϕ and the lowest college rate. For blacks, the estimated return to education, $h(\bar{e})$, is substantially lower than for other groups, offsetting the low estimate of ϕ and thus contributing to the lower college rate.

From the estimation, the mismatch comes from taste shocks. Noise in the test scores is almost irrelevant. Though the taste shock is, by construction, distributed symmetrically around zero, it generates more under-match compared to over-match. The non-linearity is, in part, arising from the logistic function. As noted earlier, mismatch is largest for black households and one source is the larger dispersion of tastes.

The "fit" measure is the sum of the percentage differences between the simulated and data moments. The fit is best for whites and relatively poor for blacks.

Table 3: Moments

	college	under-match	over-match	α_0	α_1	ν_1	ν_2	fit
			Data					
all	0.346	0.094	0.020	-3.225	0.045	0.007	0.004	na
male	0.294	0.095	0.013	-3.709	0.048	0.005	0.003	na
female	0.402	0.092	0.028	-2.873	0.043	0.009	0.006	na
white	0.397	0.082	0.040	-3.349	0.047	0.007	0.004	na
black	0.203	0.122	0.016	-3.255	0.049	0.008	0.005	na
			No BC					
all	0.276	0.080	0.022	-4.205	0.055	0.005	0.005	0.266
male	0.268	0.080	0.014	-4.514	0.059	0.004	0.003	0.192
female	0.302	0.074	0.034	-3.783	0.051	0.007	0.006	0.328
white	0.326	0.069	0.042	-3.478	0.049	0.006	0.005	0.122
black	0.248	0.091	0.017	-4.449	0.055	0.006	0.005	0.354
			Baseline BC					
all	0.292	0.084	0.021	-3.890	0.052	0.006	0.004	0.124
male	0.279	0.090	0.013	-4.045	0.053	0.005	0.003	0.036
female	0.306	0.077	0.033	-3.676	0.050	0.008	0.006	0.232
white	0.320	0.074	0.042	-3.449	0.048	0.007	0.004	0.051
black	0.227	0.105	0.017	-4.392	0.052	0.007	0.005	0.179
			Estimated No Taste Shocks: $\bar{\varepsilon} == 0$					
all	0.265	0.071	0.027	-4.551	0.059	0.009	0.003	0.736
male	0.260	0.062	0.017	-5.290	0.069	0.005	0.002	0.811
female	0.286	0.070	0.038	-3.971	0.052	0.010	0.004	0.619
white	0.319	0.067	0.045	-3.494	0.048	0.009	0.003	0.194
black	0.193	0.098	0.023	-5.454	0.063	0.009	0.002	1.075
			Estimated No Test Noise: $\sigma == 0$					
all	0.294	0.084	0.022	-3.883	0.052	0.006	0.004	0.125
male	0.279	0.090	0.013	-4.045	0.053	0.005	0.003	0.036
female	0.306	0.077	0.033	-3.676	0.050	0.008	0.006	0.232
white	0.320	0.074	0.042	-3.452	0.048	0.007	0.004	0.051
black	0.227	0.105	0.017	-4.394	0.052	0.007	0.005	0.182

This table reports data and simulated moments for the estimated models with perfect capital markets and borrowing constraints as well as some counterfactuals.

5.2 Borrowing Constraints

The next blocks in Tables 2 and 3 are for the case of (potentially) binding borrowing constraints. Specifically, this case estimates $\bar{b}$, the per period borrowing limit during the school phase as a fraction of ω_1. The estimated value of $\bar{b}$ implies that the borrowing constraint binds for some but not all types (i.e. tastes and ability) of individuals.

Comparing the last columns of Table 3 for the cases of borrowing constraints and no borrowing constraints reveals an important result: **the model is able to better match the moments with an occasionally binding**

borrowing constraint. This is the case for all of the households, where the fit goes from 0.266 in the baseline to 0.124. As noted earlier, a binding borrowing constraint creates asymmetric mismatch by increasing under-match relative to over-match. This is clear in the results for the black sub-group: the estimated model with a borrowing constraint generates an under-match rate of 10.5% and an over-match rate of only 1.7%. This is much closer to the data than the moments from the baseline model and is one of the reasons the fit is substantially better for the black group.

This finding of a borrowing constraint is consistent with other studies of educational choice using NLSY97. In particular, Belley and Lochner (2007a) contrast the role of family income and family characteristics in the NLSY79 versus the NLSY97 samples. They find that family income is much more important in the NLSY97 sample and interpret this as evidence of capital market frictions. We return to uncovering the role of family income and other characteristics of parents in Section 6.

The estimates of $\bar{b}$ vary considerably across the sub-groups. From Table 2, the black group faces a very severe borrowing constraint as $\bar{b}$ is essentially zero. In contrast, males have a relatively large estimated value of $\bar{b}$. The key though is not these values *per se* but the effect of the borrowing constraint on the moments, such as the mismatch patterns and the education rates.

Understanding the results for blacks is revealing about the mechanics of the model. The estimate of ϕ for blacks is much lower and thus the mean ability much higher compared to other groups. At the same time, the coefficients from the logistic regression are about the same for all groups. Finally, the college rate is much lower for blacks and the mismatch rate much higher. In the absence of a borrowing constraint, the low attainment rate is "explained" by a very low estimate of the returns to education, $h(\bar{e}) = 0.381$, and a large variance in taste shocks. From Table 3, this parameterization does indeed yield both a low college rate and sizable mismatch.

With the introduction of a borrowing constraint, the estimated return to college rises to 0.442, and more under-match is produced. The constraint binds enough to reduce the college rate by about 2 percentage points.

The bottom panels of Tables 2 and 3 highlight the roles of the taste shocks and the test noise. In these experiments, there is either no taste shock, $\bar{\varepsilon} == 0$ or no noise in the test score, $\sigma == 0$. The models are not re-estimated under these restrictions: these are simulations under alternative parameterizations.

The parameter moments for the case of $\sigma == 0$ are very close to the baseline. In this sense, the noise in the test score is irrelevant.

This is not the case for the taste shocks. Setting $\bar{\varepsilon} == 0$ has a noticeable influence on the other parameter estimates and on the moments. From Table 2, eliminating the taste shocks provides a larger role for the noisy test score, partly to generate mismatch. From Table 3, this does indeed happen but the fit is not nearly as good as in the baseline, particularly for males and blacks. Interestingly this model is able to produce considerable under- match relative to over-match, particularly for blacks. But the noisy test score has a cost: this model does not do as good of a job, again referring to the black sub-group, of matching the ν_2 coefficients in the wage regression since the test score is less correlated with ability.

As seen in Table 20 in section 9, these same findings apply to the baseline model without borrowing constraints. That is, the test score is relatively unimportant and the taste shock crucial for matching moments even if there is no binding borrowing constraint.

To be clear, the presence of a borrowing constraint does not mean it binds for all households. For this discussion,

Table 4: Incidence of Borrowing Constraints

	ability	taste
all	0.257	-0.164
male	0.771	-0.218
female	-12.333	-1.148
white	-32.128	-2.562
black	-3.242	-0.533

This table reports coefficient estimates from a logit regression where the dependent variable = 1 iff the education choice changed due to a binding borrowing constraint. The covariates included the agent's ability and taste shock.

a binding borrowing constraint means that the household education choice switched to no education because of the borrowing constraint.

By definition, the constraint is likely to bind for households with ability high enough to rationalize college with perfect capital markets but for whom the borrowing constraint makes education too costly. Also, it can bind for relatively low ability households who draw a high taste shock. These households may choose college and use earnings over the middle and late period to support consumption during the education phase. But the borrowing constraint implies that the gains from education, which are not that large due to their relatively low ability, are not enough to compensate for the unequal consumption.

Table 4 studies the determinants of a binding borrowing constraint. The table contains coefficient estimates for the covariates listed in the columns where the dependent variable was whether the borrowing constraint was binding or not. For all the groups, an increase in the taste for education reduces the likelihood of the constraint binding. Logically, for those with high tastes, the desire for more education overcomes the cost of not being able to smooth consumption.

For some groups the coefficient on ability is positive, it is negative for others. As discussed Lochner and Monge-Naranjo (2011), in the presence of a borrowing constraint, the influence of ability on education attainment is influenced by two forces. First, high ability agents have higher future earnings and thus want to obtain more education. This would imply that the coefficient on ability in Table 4 would be negative. Second, high ability agents want to borrow more and the binding constraint reduces the return to education and thus can generate a positive coefficient on ability.

Table 5 explores the impact of the borrowing constraint on college choice. From this table, for all households, at the estimated parameters, the education rate without the borrowing constraint would be 32.0% while the college rate falls to 29.2% once the constraint is imposed. For black households, the borrowing constraint reduces the college rate from 32.3% to 22.7%.

5.3 Identification

Table 6 reports the elasticities of the moments with respect to the parameters. These are computed at the baseline estimates for the pooled sample with an occasionally binding borrowing constraint.[12]

[12] At the baseline, each of the parameters is varied, the model is resolved and the moments are recomputed. In doing so, the 20th and 80th percentiles of the distribution of predicted educational attainment changes since the logistic regression from (1) adjust. Thus the

Table 5: Impact of Borrowing Constraints

	College Attainment Rates		
	Data	no BC	BC
all	0.346	0.320	0.292
male	0.294	0.319	0.279
female	0.402	0.410	0.306
white	0.397	0.507	0.320
black	0.203	0.323	0.227

This table reports the effects of borrowing constraints by comparing the fraction choosing college education with perfect capital markets (no BC) and with borrowing constraints (BC) at the estimated parameters.

The first row shows how the simulated moments response to variations in the parameter of the ability distribution, ϕ. An increase in ϕ reduces the mean of the ability distribution and thus reduces the college rate. At this lower college attainment rate there is more under-match and less over-match. Changes in the distribution of ability also reduce the response of the education decision and wages to the test score.

Variations in the range of taste shocks impacts the over-match rate and, to a much less degree, the under-match rate as well. An increase in the variability of tastes increases the college rate since, all else the same, more variability means that a higher fraction of draws exceed the threshold of putting someone into college. From the perspective though of the test score, these are over-matched individuals. Since education is less responsive to the test score α_1 falls. Interestingly, conditional on education the response of wages to the test score increases substantially.

At this parameter estimate there was essentially no noise in the test score. Apparently, variation in σ has almost no local impact on the moments. Clearly once the taste shock is shut-down, as in Table 2, then the noise in the test becomes more relevant in matching moments.

The return to education, not surprisingly, impacts the college attainment rate. As the college rate increases, the under-match rate falls and the over-match rate rises. This pattern of higher college attainment being correlated with a lower under-match rate and a higher over-match rate was observed across countries as reported in Cooper and Liu (2016). The regression coefficients are also sensitive to the return to education: (i) the test score is less important in the logistic regression and (ii) wages become more responsive to the test score.

Finally, an increase in the borrowing limit lead the college rate to increase as well. The effect on mismatch is symmetric: both the under-match and over-match rates fall with an increase in the borrowing limit. In this case, wages become more responsive to test scores.

The channels through which these parameters operate are complex. What should be clear from the table is that, with the exception of the noise in the test score, locally the variation in parameters has a relatively large influence on the moments.

under-match and over-match rates adjust both because decisions change and because the cut-offs change. The Appendix provides these matrices for the sub-groups.

Table 6: Elasticities of Moments

parameter	college	under-match	over-match	α_0	α_1	ν_1	ν_2
ϕ	-0.893	1.830	-0.320	0.127	-0.334	-2.163	-2.387
$\bar{\varepsilon}$	0.673	0.684	7.297	-1.930	-1.860	0.087	1.303
σ	0.000	0.000	0.004	-0.002	-0.002	0.000	0.000
$h(\bar{e})$	2.362	-1.356	10.131	-3.836	-2.923	2.181	3.463
$\bar{b}$	0.292	-0.150	-0.280	0.003	0.160	0.080	0.199

This table reports elasticities of moments with respect to parameters for the baseline model with borrowing constraints for the pooled sample.

5.4 Across Groups

This section studies which of the differences in parameters across the groups is more important for the observed patterns in moments. We study this through counterfactuals in which one of the parameters for each group is replaced by the estimates from the "all" case. The remaining parameters are kept at their estimated values as indicated in Table 7. This exercise allows us to gauge the importance of each of the "behavioral" parameters individually. We are particularly interested in understanding which parameters are responsible for the observed differences in mismatch.

The results for the baseline model with borrowing constraints are displayed in Table 8. For all groups, the differences in ϕ are important. As indicated in the 'Same Ability' block, when all groups are forced to have the same ability parameter the fit deteriorates, particularly for males and blacks. Recall that blacks had the lowest estimate of ϕ so that the higher value of this parameter, and thus a lower mean of the ability distribution, reduces the college rate. This increases the under-match rate. The effect of this change is in the opposite direction of males: increasing the college rate and thus reducing the under-match rate. For females, who have the second lowest estimate of ϕ, this parameter change has the smallest impact on the fit.

Imposing the same tastes also has a very large impact on males and blacks. Making the taste distribution the same, reduces the range for blacks and increases it for males. Again, the black college rate falls and it rises for the males relative to the baseline. Whites also have a sizable reduction in fit, with an increase in the education rate as well as in the mis-match rates.

Imposing the same return from college, $h(\bar{e}) = 0.690$, leads to relatively large changes in the fit except for females. The college rate rises considerably for blacks, as does the over-match rate. In contrast, the white college rate falls and there is considerable under-match.

Finally, imposing the same borrowing limit has a considerable impact on females, whites and blacks. Surprisingly, the under-match rate does not respond very much relative to the over-match rate.

From the perspective of understanding mismatch, the key to understanding the differences across groups stems largely from differences in tastes. Relative to the baseline estimates, reducing the dispersion in tastes, as in the case of females and blacks, leads to a reduction in mismatch. Increasing the dispersion of tastes, as in males, implies large increase in mismatch. The differences in returns to education are also very important for the mismatch of the black sub-group. Increasing the return, as in the same $h(\bar{e})$ treatment, reduces the under-match but leads to a much higher over-match rate.

Table 7: Parameter Estimates: Comparing Groups

	ϕ	$\bar{\varepsilon}$	σ	$h(\bar{e})$	$\bar{b}$
			Baseline		
all	2.610	12.435	0.010	0.690	0.775
male	3.593	8.644	0.002	0.810	0.796
female	2.173	16.393	0.000	0.688	0.371
white	3.040	11.088	0.009	0.903	0.231
black	1.595	24.951	0.006	0.442	0.044
			Same Ability		
all	2.610	12.435	0.010	0.690	0.775
male	2.610	8.645	0.002	0.810	0.796
female	2.610	16.393	0.000	0.688	0.371
white	2.610	11.088	0.009	0.903	0.231
black	2.610	24.951	0.006	0.442	0.044
			Same Tastes		
all	2.610	12.435	0.010	0.690	0.775
male	3.593	12.435	0.002	0.810	0.796
female	2.173	12.435	0.000	0.688	0.371
white	3.040	12.435	0.009	0.903	0.231
black	1.595	12.435	0.006	0.442	0.044
			Same $h(\bar{e})$		
all	2.610	12.435	0.010	0.690	0.775
male	3.593	8.645	0.002	0.690	0.796
female	2.173	16.393	0.000	0.690	0.371
white	3.040	11.088	0.009	0.690	0.231
black	1.595	24.951	0.006	0.690	0.044
			Same borrowing limit		
all	2.610	12.435	0.010	0.690	0.775
male	3.593	8.645	0.002	0.810	0.775
female	2.173	16.393	0.000	0.688	0.775
white	3.040	11.088	0.009	0.903	0.775
black	1.595	24.951	0.006	0.442	0.775

This table reports parameter values with some parameters held constant across the groups. There is no re-estimation of the other parameters. These estimates are for the borrowing constraint case.

5.5 Robustness

This subsection studies the robustness of our findings to calibrated parameters. In particular, the baseline model assumed log utility and imposed a college cost of 25% of the compensation received by young workers. Here we consider a CRRA representation of utility, $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$, with the parameter $\gamma = 2$, as in Johnson (2013). Further we consider a higher cost of education, increasing the price by 20%. Finally, we replace the weighting matrix with the inverse of the variances from the various moments, with the covariances fixed at zero.

The results, for both the case of perfect capital markets and the model with borrowing constraints are reported in Tables 21 and 22, found in the Appendix. There are two key findings.

First, as with the baseline parameters, noise in the test score plays essentially no role. That is, the estimated value of σ is near zero for all the cases. Instead, mismatch comes from either the taste shock or, in some cases, occasionally binding borrowing constraints.

Table 8: Moments: Comparing Groups

	college	under-match	over-match	α_0	α_1	ν_1	ν_2	fit
			Baseline					
all	0.292	0.084	0.021	-3.890	0.052	0.006	0.004	0.124
male	0.279	0.090	0.013	-4.045	0.053	0.005	0.003	0.036
female	0.306	0.077	0.033	-3.676	0.050	0.008	0.006	0.232
white	0.320	0.074	0.042	-3.449	0.048	0.007	0.004	0.051
black	0.227	0.105	0.017	-4.392	0.052	0.007	0.005	0.179
			Same Ability					
all	0.292	0.084	0.021	-3.890	0.052	0.006	0.004	0.124
male	0.364	0.040	0.018	-3.861	0.059	0.008	0.006	2.047
female	0.263	0.099	0.036	-3.695	0.046	0.005	0.004	0.520
white	0.358	0.054	0.041	-3.425	0.051	0.009	0.006	0.316
black	0.140	0.146	0.014	-4.732	0.047	0.001	0.002	1.462
			Same Tastes					
all	0.292	0.084	0.021	-3.890	0.052	0.006	0.004	0.124
male	0.349	0.110	0.093	-2.139	0.028	0.005	0.004	40.890
female	0.258	0.061	0.000	-6.567	0.087	0.008	0.004	4.067
white	0.341	0.082	0.067	-2.796	0.039	0.007	0.005	0.539
black	0.142	0.087	0.000	-17.444	0.203	0.007	0.001	30.824
			Same $h(\bar{e})$					
all	0.292	0.084	0.021	-3.890	0.052	0.006	0.004	0.124
male	0.158	0.107	0.000	-8.591	0.099	0.003	0.001	4.784
female	0.308	0.076	0.035	-3.639	0.050	0.008	0.006	0.239
white	0.144	0.107	0.000	-9.915	0.113	0.004	0.001	8.225
black	0.392	0.083	0.095	-2.111	0.032	0.013	0.010	27.284
			Same borrowing limit					
all	0.292	0.084	0.021	-3.890	0.052	0.006	0.004	0.124
male	0.275	0.090	0.013	-4.040	0.052	0.005	0.003	0.036
female	0.382	0.075	0.077	-2.418	0.036	0.009	0.007	3.219
white	0.449	0.062	0.106	-1.751	0.030	0.008	0.006	3.349
black	0.309	0.093	0.053	-3.108	0.041	0.008	0.008	6.135

This table reports moments with some parameters held constant across the groups. There is no re-estimation of other parameters. These moments are for the borrowing constraint case.

Second, the models with borrowing constraints fits better than those with perfect capital markets. For the case of the higher cost of education, this gain is large for the male and black sub-groups. However, for the higher risk aversion case, the fit improves only marginally. Evidently the higher risk aversion reduces the impact of the borrowing constraint.

Interestingly, the risk aversion matters even in the case of perfect capital markets. Essentially changes in the curvature affects the gain to college, $V^c - V^n$, relative to the additive taste shock. Thus the moments differ from the baseline estimates without a borrowing constraint.

The last experiment replaces (19) with a weighting matrix equal to the inverse of a matrix with the variances of the moments along the diagonal. This objective is given in (20).

$$min_{\Theta}(M^d - M^s(\Theta))W(M^d - M^s(\Theta))'. \tag{20}$$

This weighting matrix puts considerably more weight on matching the coefficients from the wage regression. The same patterns in estimates and moments remain. The noise in the test score remains small. Second, there is again an improvement in fit once the borrowing constraint is introduced.

6 Role of Parents

This section studies the influence of parents on education choice and thus mismatch. It returns to the motivation of distinguishing between the transfer of resources and of direct influence of parents on children through tastes and/or ability: i.e. "money or grit?". Here, again, the term "grit" aptly captures non-cognitive influences of parents on the work habits, determination and even role models. As the analysis develops, we also allow parents to influence the ability and/or tastes of their offspring. A key point is again understanding the determinants of mismatch.

Our initial finding that the model with borrowing constraints fits the moments better than the model with perfect capital markets implies that the first of these channels could be operative. The point of this section is to allow other forms of interaction between parents and offspring and to determine the importance of borrowing constraints for educational attainment and mismatch.

There are two channels linking educational attainment with parent's characteristics: (i) the provision of resources and (ii) the creation of environments for the accumulation of human capital (both cognitive and non-cognitive skills).[13] There is a large extant literature on the relative importance of these links between parents and education attainment. Looking at the NLSY 1979 sample, Cameron and Heckman (2001), and Carneiro and Heckman (2002) argue that the second channel is the main way in which parents influence the education outcome of their children. Specifically, Carneiro and Heckman (2002) conclude "at most 8% of American youth are subject to short term liquidity constraints that affect their post-secondary schooling."

Belley and Lochner (2007a), looking at the NLSY97 sample, argue that the role of family income has increased over time, partly due to increased tuition between the samples. From their Table 3, both family income and family characteristics, such as the parent's educational attainment, are significant in explaining education for the NLSY97 sample. In fact, the coefficient in the reduced form regression on family income is considerable higher in the NLSY97 sample compared to the NLSY79 sample.

We study these issues in our model in a couple of ways. First, in sub-section 6.1, we extend the model to include outside family income or transfers. The moments we match are supplemented by allowing these flows to influence educational attainment. In one specification, the resource flow is correlated with ability in the model allowing us to match a correlation between the flow and test score in the data. For this extended model the borrowing constraint continues to matter.

Sub-section 6.2 studies the impact of parent's education on either the child's tastes or ability. Here we correlate parent's education with either the taste shock or ability and match, in the latter case, an additional moment linking parent's education to test scores. **The estimated model without capital market imperfections matches the moments very well. Adding in the borrowing constraint does not improve the fit of the model.** Further, in this case, while there is some noise in the test score, the main factor creating mismatch remains taste shocks.

[13] See Cunha, Heckman, and Schennach (2010) and the references therein.

6.1 Family Income and Transfers

This section studies the impact of family resources on the chid's educational attainment and mismatch. Flows from parents were not explicitly incorporated into the educational choice problem specified above. Here we introduce those flows into the model and then re-estimate parameters.

Consider an extension of our model to include a transfer from parents, received at the start of the education phase.[14] The household head chooses transfers to a child, denoted Z, that solves $max_Z u^p(Y-Z)+\lambda V(Z,\theta)$ with $u^p(\cdot)$, strictly increasing and strictly concave, representing the parents utility given income Y and $V(Z,\theta)$ being the indirect utility of a child with resources Z and ability θ. This value comes from the college choice problem studied in section 3 with Z added to the resources in (17). The parameter λ is a weight between the parents consumption and the value of the child's optimization problem. The optimal transfer will be increasing in parent's income.[15]

Though this model is not included explicitly in the estimation, it frames the analysis that follows. The next sub-section considers the effect of family income on college choice. As argued above, the optimal transfer will depend on family income. It is common in the literature on the empirical effects of family income on education choice to treat family income as representing the resources available to the child. The reduced form estimates reported in this section on the dependence of educational attainment on family income provide a useful comparison with these previous findings.

Following Johnson (2013), the second sub-section studies transfers directly. While the sample is smaller, the measure of the resource flow is more direct. For that analysis, both the model and the moments are expanded to study the effects of family resources through transfers from parents on educational outcomes. We study these flows allowing either a correlation between transfers and ability or between transfers and tastes. Accordingly, the estimation matches two additional types of moments. First, we include regression coefficients linking transfers to educational attainment. Second, we include the correlation between transfers and the child's test score for part of the analysis.

For both cases, we find that again the model with borrowing constraints fits the moments better. Further, there taste shocks remain substantial while the noise in test scores remains relatively low.

6.1.1 Family Income

This section studies the effects of family income on educational attainment and mismatch. The estimation includes an additional set of moments that link family income to educational attainment.

Specifically, a version of the logistic regression, (1), is estimated where both family income and the test score are used as covariates:

$$Pr(e_i=1)=\frac{exp^{\alpha_0^r+\alpha_1^r a_i+\mu_2^r inc_i^2+\mu_3^r inc_i^3+\mu_4^r inc_i^4}}{1+exp^{\alpha_0^r+\alpha_1^r a_i+\mu_2^r inc_i^2+\mu_3^r inc_i^3+\mu_4^r inc_i^4}}.^{16} \tag{21}$$

As in Belley and Lochner (2007a), family income is included through dummy variables indicating the quartile of the income distribution. But, in contrast to Belley and Lochner (2007a), the dependent variable is educational

[14] Appendix B of Belley and Lochner (2007b) outlines a more elaborate model along the same lines. Of course, the transfer may take many forms. As in Glomm and Ravikumar (1992), parents may directly choose education quality for their children.

[15] This follows directly from the strict concavity of $u^p(\cdot)$ and the curvature of $V(Z,\theta)$ with respect to Z. The dependence of the transfer on ability is complicated by both the education decision as well as the potentially binding borrowing constraint.

[16] Weaker results obtain when using a measure of wealth rather than family income. In keeping with the literature, such as Belley and Lochner (2007a), we focus on family income and not wealth.

Table 9: Parameter Estimates: Family Income

	ϕ	$\bar{\varepsilon}$	σ	$h(\bar{e})$	θ_{pinc}	$\bar{b}$
	No Correlation					
	No BC					
all	1.693	24.624	0.000	0.348	na	na
male	1.905	21.040	0.003	0.384	na	na
female	1.641	24.948	0.034	0.363	na	na
white	1.614	23.726	0.249	0.357	na	na
black	1.676	23.605	0.015	0.369	na	na
	BC					
all	1.560	24.939	0.022	0.333	na	0.062
male	2.611	13.141	0.000	0.614	na	0.059
female	1.495	24.999	0.022	0.364	na	0.110
white	1.906	16.818	0.322	0.515	na	0.171
black	1.781	20.267	0.018	0.444	na	0.003
	Correlated Income and Ability					
	ϕ	$\bar{\varepsilon}$	σ	$h(\bar{e})$	θ_{pinc}	$\bar{b}$
	No BC					
all	4.588	16.426	0.245	0.777	0.930	na
male	4.414	14.368	0.051	0.760	0.523	na
female	2.741	15.550	0.483	0.737	0.975	na
white	3.024	10.034	0.648	0.784	0.725	na
black	1.915	24.859	0.022	0.432	0.447	na
	BC					
all	4.307	17.653	0.167	0.762	0.882	0.445
male	4.511	14.105	0.002	0.830	0.400	0.037
female	2.266	20.247	0.436	0.614	0.957	0.246
white	2.400	10.930	0.510	0.719	0.314	0.116
black	1.849	24.937	0.002	0.459	0.488	0.001

This table reports parameter estimates for a model in which family income influences educational attainment.

attainment not enrollment. The regression coefficients are denoted μ_j^r where j is the index of the quartile (with $j = 1$ excluded). The test score is continuous with a coefficient of α_1^r in the regression with family income as additional covariates.

Note that the additional moments use the quartile of family income as a proxy for family resources and thus transfers. Since the transfer function is monotone in income, the quartile of family income is a good proxy for the quartile of the transfer.

These results from estimation of (21), for the entire sample as well as the sub-groups, are shown in Table 10. In the data, the response of the test score is increasing in family income. This is similar to the findings in Belley and Lochner (2007a) though our coefficient estimates are larger. The coefficient on the test score in regression (21) is generally quite close to that from regression (1).

In terms of other moments, the mismatch rates continue to be determined by the initial regression, conditioning only on the test score, as in (1). Thus the regression coefficients from (21) are in addition to the original set of moments.

The simulated data are created by solving our model with the inclusion of a transfer Z. Since family income is used as a proxy for the transfer, the distribution of Z is assumed to be Pareto and a single parameter is calibrated by race and gender to match mean family income from the NLSY97 sample.

The parameter estimates are reported in Table 9 and the moments in Table 10. There are two cases explored. In the first, termed "No Correlation", parents income influences the household choice problem only through the direct provision of resources. Whether this relaxes a borrowing constraint depends on whether the borrowing constraint is imposed, as in the "BC" treatment.

The second case, termed "Correlated Income and Ability", allows parents income to influence the child's ability. This dependence of ability on the transfer from parents is parameterized by θ_{pinc}. For this treatment, an additional moment is added: the correlation between family income and the child's test score, denoted "$c(t, Y)$" in Table 10. The model links income to ability through θ_{pinc} and this is reflected in $c(t, Y)$.

In the initial block of moments in Table 10, in which the family influence is through resources only, the fit of the model is again better in the borrowing constraint (BC) case. The fit improves for every group. In particular, the estimated model in the BC case mimics very closely the influence of parent's income on education attainment for the higher quartiles but is unable to match the negative coefficients on the second quartile. Compared to the case of perfect capital markets, the BC model does better fitting most of the mismatch moments.

Once the family income influences ability as well, the results are somewhat different. The noise in the test score matters, particularly for the white and female sub-groups. The fit again improves with the addition of the borrowing constraint. Despite adding an additional moment, the fit of the model is better than the case of no correlation between family income and ability. Thus allowing family income to directly influence the budget set and indirectly affect ability fits the data better.[17]

6.1.2 Transfers

This sub-section reports estimates from a model with parental transfers. The calculation of transfers follows Johnson (2013). Here transfers take three forms: (i) money from parents, (ii) transfers while attending school and (iii) support through the provision of housing. The transfer is the sum of these flows over the years of 1997-2007.

For our sample, the correlation between family income and the transfer is 0.433. Thus the focus on transfers alone is picking up some additional variation in the data.

The simulated model underlying the estimation includes a transfer, Z, from parents. This is drawn from a Pareto distribution, allowing, in the second case, a correlation between transfers and child's ability. There are two additional parameters for this exercise. One is set to match the fraction (7%) of agents receiving a zero transfer. The second is a parameter for the Pareto distribution of the transfer, denoted aZ, and is included in the set of estimated parameters.

There are two differences in moments. First, the regression in (21) is replaced by one in which the quartile of transfer is used instead of the quartile of income. Second, the mean fraction of transfers relative to wage income, denoted μ_{tr}, is included as a moment common to all race and gender groups.

Tables 11 and 12 report the coefficient estimates from (21) when family transfers are used directly. There are a couple of key findings. First, the model allowing a correlation between transfers and ability match the moments better, including the added moment of the mean transfer. Second, the borrowing constraint improves the fits only

[17] This is consistent with the reduced form findings in Belley and Lochner (2007a) and Johnson (2013) where the regression coefficients on family income are lower when other family characteristics are included as covariates.

Table 10: Moments: Family Income

	college	under-match	over-match	α_0	α_1	ν_1	ν_2	α^r	μ_2^r	μ_3^r	μ_4^r	$c(t,Y)$	fit
Data													
all	0.346	0.094	0.020	-3.225	0.045	0.007	0.004	0.039	0.249	0.597	1.200	0.377	na
male	0.294	0.095	0.013	-3.709	0.048	0.005	0.003	0.041	0.657	0.887	1.485	0.367	na
female	0.402	0.092	0.028	-2.873	0.043	0.009	0.006	0.036	0.241	0.578	1.268	0.392	na
white	0.397	0.082	0.040	-3.349	0.047	0.007	0.004	0.041	0.313	0.892	1.359	0.262	na
black	0.203	0.122	0.016	-3.255	0.049	0.008	0.005	0.040	0.610	1.128	1.541	0.303	na
No Correlation													
	No BC												
all	0.230	0.101	0.028	-4.329	0.052	0.005	0.005	0.052	0.061	0.128	0.498	na	2.180
male	0.205	0.102	0.019	-5.176	0.061	0.004	0.004	0.061	0.055	0.111	0.545	na	2.982
female	0.255	0.095	0.036	-3.910	0.048	0.006	0.006	0.048	0.058	0.123	0.426	na	2.240
white	0.245	0.093	0.042	-4.071	0.050	0.006	0.006	0.050	0.063	0.134	0.520	na	2.197
black	0.238	0.093	0.019	-4.589	0.056	0.005	0.005	0.057	0.052	0.103	0.362	na	2.832
	BC												
all	0.222	0.103	0.025	-4.507	0.053	0.005	0.005	0.054	0.322	0.481	0.859	na	0.871
male	0.230	0.091	0.018	-4.948	0.061	0.005	0.003	0.063	0.636	0.937	1.244	na	0.729
female	0.262	0.093	0.035	-3.912	0.049	0.007	0.007	0.050	0.310	0.471	0.760	na	0.838
white	0.269	0.081	0.049	-3.866	0.049	0.007	0.005	0.050	0.380	0.555	0.846	na	0.628
black	0.239	0.094	0.020	-4.587	0.056	0.006	0.005	0.058	0.447	0.685	0.933	na	0.966
Correlated Income and Ability													
	No BC												
all	0.287	0.076	0.025	-4.141	0.055	0.006	0.004	0.045	0.230	0.665	1.067	0.515	0.495
male	0.285	0.087	0.014	-4.021	0.053	0.004	0.003	0.053	0.100	0.154	0.122	0.490	2.542
female	0.346	0.054	0.041	-3.562	0.052	0.008	0.006	0.045	0.184	0.568	1.199	0.432	0.647
white	0.339	0.064	0.052	-3.245	0.046	0.007	0.004	0.040	0.156	0.547	1.713	0.370	0.807
black	0.268	0.096	0.017	-3.932	0.050	0.005	0.005	0.050	0.065	0.110	0.050	0.326	2.922
	BC												
all	0.286	0.083	0.024	-3.992	0.053	0.005	0.004	0.045	0.273	0.604	0.900	0.520	0.446
male	0.284	0.094	0.013	-3.798	0.050	0.004	0.003	0.045	0.577	1.061	1.151	0.466	0.220
female	0.304	0.076	0.035	-3.700	0.050	0.007	0.005	0.045	0.243	0.655	1.058	0.413	0.399
white	0.300	0.071	0.048	-3.630	0.049	0.007	0.004	0.047	0.323	0.800	1.519	0.242	0.187
black	0.265	0.103	0.017	-3.794	0.047	0.006	0.005	0.047	0.326	0.591	0.615	0.331	1.055

This table reports moments for a model in which family income influences educational attainment.

Table 11: Parameter Estimates: Family Transfers

	ϕ	$\bar{\varepsilon}$	σ	$h(\bar{e})$	θ_{pinc}	aZ	$\bar{b}$
	No Correlation						
	No BC						
all	1.708	24.868	0.000	0.356	4.847	na	na
male	2.120	22.052	0.000	0.397	4.667	na	na
female	1.597	24.974	0.000	0.375	4.886	na	na
white	3.049	11.610	0.004	0.754	8.493	na	na
black	1.177	10.270	2.872	0.305	5.054	na	na
	BC						
all	1.657	24.734	0.000	0.358	4.845	na	0.241
male	2.020	22.008	0.001	0.397	4.347	na	0.486
female	1.561	24.999	0.001	0.374	5.919	na	0.000
white	3.030	11.622	0.016	0.743	8.454	na	0.002
black	1.177	10.262	2.872	0.305	5.054	na	2.252
	Correlated Transfer and Ability						
	ϕ	$\bar{\varepsilon}$	σ	$h(\bar{e})$	θ_{pinc}	aZ	$\bar{b}$
	No BC						
all	2.435	8.421	1.045	0.613	1.998	4.298	na
male	2.376	17.731	0.079	0.507	0.417	4.776	na
female	2.763	8.004	0.798	0.744	1.786	4.606	na
white	2.512	7.965	1.114	0.711	1.998	4.730	na
black	1.704	15.871	0.197	0.520	0.122	3.000	na
	BC						
all	2.438	8.405	1.043	0.613	1.998	4.314	1.676
male	2.375	17.697	0.078	0.507	0.418	4.791	1.526
female	2.763	8.004	0.799	0.744	1.786	4.605	1.507
white	2.512	7.965	1.114	0.711	1.998	4.730	1.500
black	1.704	15.871	0.197	0.520	0.122	3.000	1.133

This table reports parameter estimates for a model in which family transfers influences education attainment.

marginally for males and not for other sub-groups. This suggests that the transfer is not operating through the borrowing constraint. Second, there is a larger role in this specification for noise in the test score, relative to the baseline.

6.2 Parent's Education

This section studies the impact of parent's (throughout this is mother's) education on educational outcomes.[18] This is taken as an alternative to a family link based on income or transfers alone. Importantly, for our sample the correlation between family income and mother's education is around 0.2 for the pooled sample and the sub-groups. Thus we are looking at a variation in the data different from the effects of family income.

There are two avenues of influence explored. First, the parent's education impacts the tastes of the child. This is the case labeled "Correlated with Tastes" in the tables. Second, the parent's education impacts the ability of the child. This influence is measured by a correlation between parent's education and test score in the data. This is the case labeled "Correlated with Ability" in the tables.

[18] In keeping with the literature, including Belley and Lochner (2007a), the analysis isolates the effects of mother's education.

Table 12: Moments: Family Transfers

	college	under-match	over-match	α_0	α_1	ν_1	ν_2	α^r	μ_2^r	μ_3^r	μ_4^r	$c(t,Z)$	μ_{tr}	fit
Data														
all	0.346	0.094	0.020	-3.225	0.045	0.007	0.004	0.036	0.132	0.980	2.264	0.303	1.050	na
male	0.294	0.095	0.013	-3.709	0.048	0.005	0.003	0.040	0.080	0.796	2.170	0.271	1.050	na
female	0.402	0.092	0.028	-2.873	0.043	0.009	0.006	0.035	0.278	1.069	2.292	0.338	1.050	na
white	0.397	0.082	0.040	-3.349	0.047	0.007	0.004	0.035	0.299	1.374	2.632	0.322	1.050	na
black	0.203	0.122	0.016	-3.255	0.049	0.008	0.005	0.042	-0.008	0.645	1.722	0.271	1.050	na
No Correlation														
	No BC													
all	0.234	0.100	0.026	-4.279	0.051	0.005	0.005	0.052	0.069	0.082	0.130	1.185	na	2.607
male	0.199	0.112	0.013	-4.811	0.055	0.003	0.003	0.055	0.062	0.094	0.135	1.200	na	2.339
female	0.270	0.089	0.037	-3.809	0.048	0.007	0.007	0.048	0.063	0.071	0.098	1.179	na	2.979
white	0.352	0.064	0.052	-3.150	0.046	0.006	0.005	0.046	0.032	0.027	0.032	1.057	na	3.047
black	0.210	0.086	0.028	-5.331	0.064	0.010	0.004	0.064	-0.007	0.003	0.025	1.160	na	3.524
	BC													
all	0.238	0.098	0.025	-4.261	0.052	0.005	0.005	0.052	0.146	0.169	0.219	1.199	na	2.151
male	0.208	0.108	0.014	-4.730	0.055	0.003	0.004	0.055	0.089	0.125	0.179	1.232	na	2.148
female	0.268	0.090	0.036	-3.851	0.049	0.007	0.007	0.049	0.220	0.234	0.259	1.152	na	2.015
white	0.327	0.070	0.047	-3.377	0.047	0.006	0.004	0.047	0.374	0.382	0.386	1.103	na	1.582
black	0.210	0.086	0.028	-5.331	0.064	0.010	0.004	0.064	-0.007	0.003	0.025	1.160	na	3.525
Correlated Transfer and Ability														
	No BC													
all	0.298	0.072	0.029	-3.880	0.052	0.007	0.003	0.046	0.139	0.508	2.010	0.506	1.559	1.418
male	0.236	0.098	0.014	-4.521	0.055	0.004	0.003	0.055	0.066	0.092	0.078	0.342	1.285	2.257
female	0.376	0.057	0.041	-3.134	0.048	0.008	0.004	0.041	0.257	0.789	2.222	0.528	1.458	1.060
white	0.375	0.071	0.052	-2.772	0.042	0.007	0.004	0.036	0.284	0.814	2.390	0.480	1.441	0.727
black	0.312	0.048	0.020	-4.722	0.067	0.009	0.007	0.067	-0.008	0.038	0.087	0.132	1.483	3.752
	BC													
all	0.298	0.073	0.029	-3.874	0.052	0.007	0.003	0.046	0.138	0.506	2.008	0.505	1.556	1.414
male	0.236	0.098	0.014	-4.524	0.055	0.004	0.003	0.055	0.068	0.095	0.083	0.342	1.284	2.228
female	0.376	0.057	0.041	-3.134	0.048	0.008	0.004	0.041	0.257	0.789	2.222	0.528	1.458	1.060
white	0.375	0.071	0.052	-2.772	0.042	0.007	0.004	0.036	0.284	0.814	2.390	0.480	1.441	0.727
black	0.312	0.048	0.020	-4.722	0.067	0.009	0.007	0.067	-0.008	0.038	0.087	0.132	1.483	3.752

This table reports moments for a model in which either parent's transfer influences college choice.

To capture the influence of parent's education on outcomes, specifically the mother's completion of high school or not, is treated as a dummy variable, denoted pe_i, in a version of (1):

$$Pr(e_i = 1) = \frac{exp^{\alpha_0^r + \alpha_1^r a_i + \mu^p pe_i}}{1 + exp^{\alpha_0^r + \alpha_1^r a_i + \mu^p pe_i}}. \tag{22}$$

The estimates obtained from (22) are included in the moments to be matched.

In addition, for the "Correlated with Ability" model, the moments include the observed correlation between parent's education and the child's test score. There is no comparable moment for the "Correlated with Tastes" case as tastes are not directly observed, nor is a signal of them.

The parameter estimates are given in Table 13 and the moments in Table 14 in blocks depending on the channel of influence. The parameters and moments are specific to the blocks.

The estimated parameter ε_{pe} is the shift in the mean of the distribution of ε if the mother attains a high school degree. The estimated parameter θ_{pe} captures the influence of mother's education on the mean of the distribution of ability. In the simulated data, mother's education is randomly drawn to match the group specific high school attainment rates.[19]

From the discussion of the baseline models, there were two key findings. The first was the estimate of no noise in the test score. The second was the slight improvement in fit with an occasionally binding borrowing constraint.

Neither of those conclusions survives these extensions of the model. The estimated models indicate noise in the test score and there is no evidence of a binding borrowing constraint. Importantly, allowing parents education to influence either tastes or ability greatly enhances the fit of the model.

Despite matching additional moments, these are the best fitting models. This is particularly noteworthy relative to the case in which the influence within the family arises through resource flows.

As indicated in Table 13, for both models of correlation and regardless of the imposition of a borrowing constraint, the estimated of σ is much larger than the baseline estimate. Table 15 substantiates this claim by showing that the moments change considerably with $\sigma = 0$. The linking of parent's education to either tastes or ability limits the influence of these factors and thus enlarges the role played by noise in the test score for creating (measured) mismatch.

This source of mismatch is unrelated to the efficient allocation of individuals to educational attainment. It is simply noise from the perspective of the researcher.

Note that the parameters that govern the influence of parent's education on tastes (ε_{pe}) or ability (θ_{pe}) are positive. In the estimated model, an increase in mother's education either increases the taste for higher education or the ability of offspring.

The blocks labeled "No BC" and "BC" for each of the "correlated with taste" case are identical and this is the case for four of the five groups in the "correlated with ability" case, with the white sub-group being an exception. This indicates that no substantial improvement in fit was obtained by allowing an occasional borrowing constraint. The estimation of the "BC" case was conducted at numerous starting values for $\bar{b}$, searching for an improvement.

Looking at the moments in Table 14, the treatment allowing a correlation between parent's education and ability adds an additional moment from the data, the correlation between parent's education and test score. Note that the simulated model includes a link between parent's income and ability that, in part, helps to match this correlation.

[19]These rates are 78.77 (all), 79.17 (male), 78.35 (female), 75.61 (black) and 88.61 (white).

Table 13: Parameter Estimates: Parent's Education

	Correlated with Tastes					
	ϕ	$\bar{\varepsilon}$	σ	$h(\bar{e})$	ε_{pe}	$\bar{b}$
	No BC					
all	1.069	10.364	2.754	0.881	7.306	na
male	1.584	11.256	0.695	0.962	9.980	na
female	0.822	9.521	4.759	0.784	4.988	na
white	0.783	5.100	2.859	0.643	5.267	na
black	2.883	10.181	1.173	1.428	14.996	na
	BC					
all	1.069	10.364	2.754	0.881	7.306	20
male	1.584	11.256	0.695	0.962	9.980	20
female	0.822	9.521	4.759	0.784	4.988	20
white	0.783	5.100	2.859	0.643	5.267	20
black	2.883	10.181	1.173	1.428	14.996	20
	Correlated with Ability					
	ϕ	$\bar{\varepsilon}$	σ	$h(\bar{e})$	θ_{pe}	$\bar{b}$
	No BC					
all	2.740	11.615	0.502	1.591	0.484	na
male	2.228	13.325	1.256	0.949	1.303	na
female	1.188	5.744	2.090	0.976	1.152	na
white	3.054	10.227	0.459	1.431	0.649	na
black	3.565	11.678	0.620	1.475	0.547	na
	BC					
all	2.767	11.723	0.501	1.588	0.486	0.005
male	2.228	13.325	1.256	0.949	1.303	0.000
female	1.188	5.744	2.090	0.976	1.152	0.000
white	3.482	9.879	0.460	1.430	0.661	0.000
black	3.569	11.709	0.620	1.476	0.545	0.001

This table reports estimates for a model in which parent's education influences tastes or ability.

In the data, for all sub-groups, the correlation of test score and parents ability is positive. The estimated model reproduces these correlations quite well.

As is clear from this table, the fit of the model is extremely good. While the model does not nest the baseline and has an additional parameter, the fit of the moments is better.

Returning to the theme of mismatch, note that the estimated models in either the "correlated with tastes" or "correlated with ability" cases produce a substantial amount of asymmetry in mismatch. In fact, relative to the data, the models produce too much over-match. The models do a good job of matching the college rates.

7 Decomposing the College Premium

This section studies the implications of the model for the college wage premium. The difference in returns to college matters for the education choice and hence for mismatch. Here we decompose the premium, by race and gender, to understand its determinants.

To study the premium in detail we return to the wage regression, given in (3):

Table 14: Moments: Parent's Education

	college	under-match	over-match	α_0	α_1	ν_1	ν_2	α^r	μ^p	c(pe,test)	fit
					Data						
all	0.346	0.094	0.020	-3.225	0.045	0.007	0.004	0.043	0.657	0.296	na
male	0.294	0.095	0.013	-3.709	0.048	0.005	0.003	0.045	0.887	0.289	na
female	0.402	0.092	0.028	-2.873	0.043	0.009	0.006	0.041	0.540	0.305	na
white	0.397	0.082	0.040	-3.349	0.047	0.007	0.004	0.047	0.803	0.223	na
black	0.203	0.122	0.016	-3.255	0.049	0.008	0.005	0.043	0.922	0.245	na
					Correlated with Tastes						
	No BC										
all	0.327	0.062	0.064	-3.224	0.045	0.020	0.008	0.045	0.649	na	0.004
male	0.283	0.060	0.074	-3.708	0.048	0.016	0.008	0.049	0.880	na	0.005
female	0.378	0.041	0.074	-2.874	0.044	0.026	0.013	0.044	0.536	na	0.006
white	0.366	0.020	0.080	-3.347	0.051	0.023	0.014	0.051	0.801	na	0.007
black	0.212	0.131	0.064	-3.258	0.034	0.007	0.001	0.034	0.922	na	0.003
	BC										
all	0.327	0.062	0.064	-3.224	0.045	0.020	0.008	0.045	0.649	na	0.004
male	0.283	0.060	0.074	-3.708	0.048	0.016	0.008	0.049	0.880	na	0.005
female	0.378	0.041	0.074	-2.874	0.044	0.026	0.013	0.044	0.536	na	0.006
white	0.366	0.020	0.080	-3.347	0.051	0.023	0.014	0.051	0.801	na	0.007
black	0.212	0.131	0.064	-3.258	0.034	0.007	0.001	0.034	0.922	na	0.003
					Correlated with Ability						
	No BC										
all	0.354	0.058	0.048	-3.234	0.048	0.014	0.003	0.046	0.676	0.262	0.004
male	0.228	0.111	0.045	-3.696	0.042	0.010	0.002	0.040	0.860	0.319	0.008
female	0.407	0.040	0.059	-2.883	0.047	0.022	0.008	0.046	0.601	0.153	0.031
white	0.325	0.068	0.052	-3.310	0.046	0.012	0.002	0.046	0.703	0.148	0.023
black	0.241	0.116	0.060	-3.260	0.037	0.008	0.001	0.036	0.928	0.221	0.004
	BC										
all	0.351	0.060	0.048	-3.236	0.047	0.014	0.003	0.046	0.680	0.265	0.004
male	0.228	0.111	0.045	-3.696	0.042	0.010	0.002	0.040	0.860	0.319	0.008
female	0.407	0.040	0.059	-2.883	0.047	0.022	0.008	0.046	0.601	0.153	0.031
white	0.287	0.087	0.054	-3.329	0.043	0.010	0.002	0.042	0.783	0.158	0.017
black	0.241	0.116	0.060	-3.259	0.037	0.008	0.001	0.036	0.927	0.221	0.004

This table reports moments for a model in which parent's education influences tastes or ability.

Table 15: Moments: Parent's Education, Role of Noise in the Test Score

	college	under-match	over-match	α_0	α_1	ν_1	ν_2	α^r	μ^p	c(pe,test)	fit
	Correlated with Tastes										
	BC										
all	0.327	0.062	0.064	-3.224	0.045	0.020	0.008	0.045	0.649	na	0.004
male	0.283	0.060	0.074	-3.708	0.048	0.016	0.008	0.049	0.880	na	0.005
female	0.378	0.041	0.074	-2.874	0.044	0.026	0.013	0.044	0.536	na	0.006
white	0.366	0.020	0.080	-3.347	0.051	0.023	0.014	0.051	0.801	na	0.007
black	0.212	0.131	0.064	-3.258	0.034	0.007	0.001	0.034	0.921	na	0.003
	No Noise										
all	0.304	0.000	0.029	-11.018	0.158	0.027	0.010	0.161	0.802	na	60.795
male	0.216	0.019	0.069	-8.364	0.105	0.016	0.005	0.107	0.805	na	21.700
female	0.354	0.000	0.022	-11.397	0.176	0.035	0.017	0.178	0.593	na	72.703
white	0.335	0.000	0.051	-7.997	0.120	0.034	0.018	0.120	0.468	na	21.735
black	0.212	0.023	0.000	-24.852	0.315	0.013	0.001	0.393	4.263	na	477.775
	Correlated with Ability										
	BC										
all	0.351	0.060	0.048	-3.236	0.047	0.014	0.003	0.046	0.680	0.265	0.004
male	0.228	0.111	0.045	-3.696	0.042	0.010	0.002	0.040	0.860	0.319	0.008
female	0.407	0.040	0.059	-2.883	0.047	0.022	0.008	0.046	0.601	0.153	0.031
white	0.325	0.068	0.052	-3.310	0.046	0.012	0.002	0.046	0.703	0.148	0.023
black	0.241	0.116	0.060	-3.259	0.037	0.008	0.001	0.036	0.927	0.221	0.004
	No Noise										
all	0.354	0.010	0.000	-7.511	0.116	0.019	0.004	0.116	0.020	0.426	18.811
male	0.228	0.044	0.000	-11.853	0.153	0.014	0.002	0.153	-0.025	0.556	67.252
female	0.407	0.000	0.000	-23.821	0.401	0.029	0.013	0.401	-0.130	0.346	439.534
white	0.325	0.017	0.000	-7.932	0.117	0.017	0.003	0.117	0.192	0.208	21.399
black	0.241	0.049	0.000	-9.532	0.125	0.013	0.001	0.125	0.052	0.418	40.202

This table reports moments for a model in which parent's education influences tastes or ability with and without noise in the test score.

Table 16: Parameter Estimates

	ϕ	$\bar{\varepsilon}$	σ	$h(\bar{e})$	$\bar{b}$
	Baseline: $\nu_3 == 0$				
all	2.610	12.435	0.010	0.690	0.775
male	3.593	8.644	0.002	0.810	0.796
female	2.173	16.393	0.000	0.688	0.371
white	3.040	11.088	0.009	0.903	0.231
black	1.595	24.951	0.006	0.442	0.044
	Baseline: ν_3 **estimated**				
all	2.814	10.377	0.005	0.756	0.709
male	3.597	8.166	0.002	0.826	0.712
female	2.098	16.085	0.006	0.712	0.142
white	3.055	11.001	0.009	0.908	0.224
black	1.557	24.630	0.035	0.455	0.001

This table reports parameter estimates for the model with education as a covariate (ν_3) in the wage regression.

$$E[\omega_i|\cdot] = \nu_{02} + \nu_2 * test_i + \nu_3 * ed_i. \tag{23}$$

In this regression, ed_i, was a dummy variable for person i denoting college completion or not. Hence, this coefficient, from the regressions run conditional on race and gender, gives the college premium. In contrast to the baseline model, the coefficient on education, denoted ν_3, is in the set of moments matched in the estimation.

The estimates from the extended model along with the baseline estimates are given in Table 16. The moments are reported in Table 17. In this second table, the counterfactuals of "Same Ability" and "Same Return" are simulations using the estimates from the "all" case to substitute for the gender/race specific estimates.

Focus first on the ν_3 coefficient in the "Data" block of Table 17 as it provides the college premium by group. This coefficient is positive for all groups and largest for the black and female groups.

Including this moment generates the parameter estimates in the second block of Table 16. Qualitatively the parameter estimates are quite similar. The ϕ is lowest for blacks and that group has the highest taste variability, the noisiest score and the lowest return to college. As in the baseline with $\nu_3 == 0$, this group also has the tightest borrowing constraint. Males, in contrast, have the lowest mean ability, the smallest taste shock and the weakest borrowing constraint.

The fit of the expanded model is not much worse than the baseline with $\nu_3 == 0$ for females and the breakdown by race. However, the ν_3 estimate is lower for the pooled sample, males and blacks compared to the data.

Generally, the measured average college premium reflects two forces: (i) the physical return to schooling, $h(\bar{e})$ and (ii) the selection of college attainment by ability. In principal, the relative magnitude of these factor may differ across gender and race. From the model, in the early working period the college wage premium is given by $E\frac{\omega_1 h(e)\theta}{\omega_1} = h(\bar{e})E(\theta|e = \bar{e})$.

Using this expression, Table 18 shows decompositions of the college premium by gender and race. These are calculated from simulated data based upon the estimated model with ν_3 included in the moments. This analysis uses, for the two counterfactual exercises, either the same value of ϕ or $h(\bar{e})$ imposed as the "Same Ability" or "Same

Table 17: Moments

	college	under-match	over-match	α_0	α_1	ν_1	ν_2	ν_3	fit
				Data					
all	0.346	0.094	0.020	-3.225	0.045	0.007	0.004	0.318	na
male	0.294	0.095	0.013	-3.709	0.048	0.005	0.003	0.311	na
female	0.402	0.092	0.028	-2.873	0.043	0.009	0.006	0.359	na
white	0.397	0.082	0.040	-3.349	0.047	0.007	0.004	0.352	na
black	0.203	0.122	0.016	-3.255	0.049	0.008	0.005	0.363	na
				Baseline: $\nu_3 == 0$					
all	0.292	0.084	0.021	-3.890	0.052	0.006	0.004	na	0.124
male	0.279	0.090	0.013	-4.045	0.053	0.005	0.003	na	0.036
female	0.306	0.077	0.033	-3.676	0.050	0.008	0.006	na	0.232
white	0.320	0.074	0.042	-3.449	0.048	0.007	0.004	na	0.051
black	0.227	0.105	0.017	-4.392	0.052	0.007	0.005	na	0.179
				Baseline: ν_3 estimated					
all	0.299	0.072	0.021	-3.878	0.052	0.006	0.004	0.240	0.211
male	0.267	0.082	0.013	-4.129	0.053	0.005	0.003	0.248	0.098
female	0.299	0.079	0.034	-3.724	0.050	0.008	0.006	0.351	0.241
white	0.320	0.074	0.042	-3.453	0.048	0.007	0.004	0.352	0.051
black	0.229	0.103	0.017	-4.446	0.053	0.007	0.005	0.309	0.212
				Same Ability					
all	0.299	0.072	0.021	-3.878	0.052	0.006	0.004	0.240	0.211
male	0.353	0.034	0.018	-4.060	0.061	0.009	0.006	0.303	2.198
female	0.248	0.105	0.037	-3.738	0.045	0.005	0.004	0.264	0.688
white	0.359	0.054	0.040	-3.428	0.051	0.009	0.006	0.383	0.337
black	0.137	0.146	0.016	-4.795	0.047	0.001	0.002	-0.052	2.773
				Same Return					
all	0.299	0.072	0.021	-3.878	0.052	0.006	0.004	0.240	0.211
male	0.140	0.118	0.000	-9.398	0.106	0.003	0.001	0.309	5.929
female	0.280	0.081	0.023	-4.094	0.054	0.008	0.005	0.359	0.391
white	0.141	0.108	0.000	-10.190	0.116	0.004	0.001	0.442	8.835
black	0.382	0.082	0.090	-2.233	0.033	0.013	0.010	0.379	24.005

This table reports data and simulated moments for the estimated model adding the education coefficient in the log wage regression as a moment, denoted ν_3. The counterfactuals are simulated, not re-estimated.

Return" cases respectively.

There are a couple of key points from this table. First the college wage premium is largest for blacks and smallest for males. This is consistent with the estimates of ν_3 from the data. Second, the estimated return to education is just the opposite: lowest for blacks and much higher for males. This difference is reconciled by selection. The mean of ability for college education relative to no college is about 3.5 for blacks and only about 1.51 for males. It is 1.57 for whites. This selection effect is also clear from the conditional means of test scores, given in the last two columns.

The two counterfactuals shown in Table 18 make clear how the college premium and the selection depends on differences in ability and return. The moments from these counterfactuals are shown in Table 17. These models do not fit as well as the baseline, with the imposition of the same returns generating the largest deterioration.

Imposing the same ability reduces the wage premium for blacks considerably though the selection effect remains strong. The premium for males rises and the selection effect is stronger.

Imposing the same return provides another perspective on the decomposition of the wage premium. In this case,

Table 18: Decomposing the College Wage Premium

	college prem.	$h(\bar{e})$	$E(\theta \mid e=\bar{e})$	$E(\theta \mid e=0)$	$E(test \mid e=\bar{e})$	$E(test \mid e=0)$
	Baseline					
all	1.655	0.756	2.190	1.282	73.216	40.116
male	1.521	0.826	1.841	1.220	74.307	41.131
female	2.185	0.712	3.067	1.423	72.587	40.388
white	1.802	0.908	1.985	1.255	71.367	39.964
black	2.849	0.455	6.259	1.759	75.587	42.394
	Same Ability					
all	1.761	0.756	2.330	1.294	73.038	39.243
male	1.894	0.826	2.293	1.259	73.409	37.251
female	1.715	0.712	2.407	1.365	72.559	42.563
white	2.033	0.908	2.239	1.278	71.108	38.156
black	1.209	0.455	2.656	1.460	76.303	45.826
	Same Return					
all	1.658	0.690	2.402	1.299	79.351	41.205
male	1.521	0.690	2.204	1.253	86.523	44.031
female	2.180	0.690	3.160	1.430	74.130	40.618
white	1.791	0.690	2.596	1.307	87.250	43.910
black	3.182	0.690	4.612	1.662	65.023	40.703

The college premium is the ratio of earnings in the late work phase for agents with college and without and $h(\bar{e})$ is the estimated return to college independent of ability. These calculations are from the estimated model with borrowing constraints, adding ν_3 as a parameter.

the selection effect is reduced for blacks to compensate for the increased return to college. Likewise, the selection effect is larger for the whites as the return is lowered.

8 Conclusion

This paper studies the determinants of mismatch using the NLSY97 sample. There are a couple of key findings.

First, the mismatch is largely a consequence of variations in tastes for education rather than noise in the test score. In this case, mismatch does not necessarily signal inefficiency. Second, a model with occasionally binding (estimated) borrowing constraints fits the data slightly better than a model without capital market frictions.

Third, the influence of parents arises largely through tastes rather than through the relaxation of a borrowing constraint. That is, once parent's education is taken into account, there is no evidence of a binding borrowing constraint. In this case, the mismatch arises solely from variations in tastes.

There is an open issue, unresolved within the model, about the implications of mismatch. At one extreme, tastes represent exogenous influences on the choice of an agent. From this perspective, the optimal allocation conditions jointly on tastes and ability and the resulting assignment to educational attainment is efficient. Measured mismatch reflects the neglect of tastes in determining education choice and is not a measure of inefficiency.

At the other extreme, tastes themselves may reflect social interactions. Put differently, taste differences may reflect social capital accumulation influenced by peers.[20] Someone with very high ability brought up in a setting where college attainment is not highly valued may choose not to attend college. In this case, an efficient allocation

[20] See Durlauf and Fafchamps (2006) and the references therein for models along these lines.

might indeed assign that person to a higher level of education attainment to avoid the loss of an under-match.

One natural extension of the analysis is, as in Dillon and Smith (2013), to consider variations in college quality as another dimension of mismatch. In this case, mismatch may arise from the assignment of low (high) ability individuals to high (low) quality schools.

9 Appendix

The tables here provide further estimation and simulation results for the models discussed above.

Table 19: Parameter Estimates: Perfect Capital Markets

	ϕ	$\bar{\varepsilon}$	σ	$h(\bar{e})$	$\bar{b}$
	No BC Baseline				
all	2.318	16.871	0.019	0.567	
male	3.594	10.757	0.000	0.740	
female	1.928	19.788	0.004	0.515	
white	2.844	13.191	0.004	0.704	
black	1.676	24.940	0.001	0.381	
	No Taste Shocks: $\bar{\varepsilon} == 0$				
ll	2.318	0.000	0.019	0.567	
male	3.594	0.000	0.000	0.740	
female	1.928	0.000	0.004	0.515	
white	2.844	0.000	0.004	0.704	
black	1.676	0.000	0.001	0.381	
	No Test Noise: $\sigma == 0$				
all	2.318	16.871	0.000	0.567	
male	3.594	10.757	0.000	0.740	
female	1.928	19.788	0.000	0.515	
white	2.844	13.191	0.000	0.704	
black	1.676	24.940	0.000	0.381	

This table reports parameters for the baseline, no taste shocks and the no test noise cases.

Table 20: Moments: No Borrowing Constraint

	college	under-match	over-match	α_0	α_1	ν_1	ν_2	fit
				Data				
all	0.346	0.094	0.020	-3.225	0.045	0.007	0.004	na
male	0.294	0.095	0.013	-3.709	0.048	0.005	0.003	na
female	0.402	0.092	0.028	-2.873	0.043	0.009	0.006	na
white	0.397	0.082	0.040	-3.349	0.047	0.007	0.004	na
black	0.203	0.122	0.016	-3.255	0.049	0.008	0.005	na
				Baseline: No BC				
all	0.276	0.080	0.022	-4.205	0.055	0.005	0.005	0.266
male	0.268	0.080	0.014	-4.514	0.059	0.004	0.003	0.192
female	0.302	0.074	0.034	-3.783	0.051	0.007	0.006	0.328
white	0.326	0.069	0.042	-3.478	0.049	0.006	0.005	0.122
black	0.248	0.091	0.017	-4.449	0.055	0.006	0.005	0.354
				No Taste Shocks: $\bar{\varepsilon} == 0$				
all	0.172	0.034	0.000	-404.766	4.889	0.006	0.001	27302.959
male	0.170	0.003	0.000	-11217.569	135.224	0.004	0.000	17171956.906
female	0.193	0.009	0.000	-2012.599	24.938	0.007	0.001	824525.431
white	0.215	0.000	0.000	-928.986	11.828	0.006	0.001	139770.520
black	0.144	0.001	0.000	-25216.569	294.560	0.006	0.001	96723440.211
				No Test Noise: $\sigma == 0$				
all	0.276	0.080	0.022	-4.215	0.055	0.005	0.005	0.265
male	0.268	0.080	0.014	-4.514	0.059	0.004	0.003	0.193
female	0.302	0.074	0.034	-3.783	0.051	0.007	0.006	0.330
white	0.326	0.069	0.042	-3.478	0.049	0.006	0.005	0.123
black	0.248	0.091	0.017	-4.449	0.055	0.006	0.005	0.355

This table reports simulated moments for the no BC case, no taste shocks and no noise models.

Table 21: Parameter Estimates: Robustness

	ϕ	$\bar{\varepsilon}$	σ	$h(\bar{e})$	$\bar{b}$
	Baseline				
	No BC				
all	2.318	16.871	0.019	0.567	na
male	3.594	10.757	0.000	0.740	na
female	1.928	19.788	0.004	0.515	na
white	2.844	13.191	0.004	0.704	na
black	1.676	24.940	0.001	0.381	na
	BC				
all	2.610	12.435	0.010	0.690	0.775
male	3.593	8.644	0.002	0.810	0.796
female	2.173	16.393	0.000	0.688	0.371
white	3.040	11.088	0.009	0.903	0.231
black	1.595	24.951	0.006	0.442	0.044
	Higher Risk Aversion				
	No BC				
all	2.267	19.249	0.022	0.611	na
male	3.767	10.420	0.002	0.793	na
female	1.938	21.248	0.006	0.591	na
white	2.889	13.363	0.001	0.751	na
black	1.844	24.965	0.105	0.499	na
	BC				
all	2.436	17.329	0.005	0.647	1.558
male	3.293	12.509	0.016	0.737	1.378
female	1.988	20.413	0.007	0.603	0.005
white	3.222	11.359	0.033	0.797	0.553
black	1.852	24.998	0.085	0.505	0.037
	Higher Cost of Education				
	No BC				
all	2.324	17.020	0.019	0.577	na
male	3.609	10.583	0.001	0.759	na
female	1.953	19.599	0.000	0.533	na
white	2.945	12.864	0.010	0.727	na
black	1.737	24.575	0.000	0.401	na
	BC				
all	2.568	12.926	0.000	0.689	0.826
male	3.567	8.912	0.002	0.814	0.839
female	2.119	16.943	0.006	0.683	0.385
white	3.046	11.308	0.009	0.903	0.317
black	1.613	24.950	0.006	0.459	0.082
	Diagonal Weighting Matrix				
	No BC				
all	2.144	17.783	0.050	0.595	na
male	3.576	11.555	0.013	0.742	na
female	1.619	21.571	0.058	0.541	na
white	2.372	13.303	0.008	0.707	na
black	2.809	23.313	0.031	0.469	na
	BC				
all	2.524	12.942	0.075	0.708	0.978
male	3.718	8.881	0.013	0.816	0.858
female	2.164	14.424	0.000	0.698	1.030
white	2.501	11.012	0.013	0.899	0.296
black	2.209	24.882	0.050	0.428	0.422

This table reports parameter estimates for alternative values of calibrated parameters. For the "higher risk aversion" case, the curvature of the CRRA utility function is set at 2. For the "Higher Cost of Education" case, tuition is 20% higher than the baseline. The "Diagonal Weighting Matrix" cases uses the inverse of the variances of the moments as a weighting matrix. These estimates are for the cases without and with a borrowing constraint.

Table 22: Moments: Robustness

	college	under-match	over-match	α_0	α_1	ν_1	ν_2	fit
			Baseline					
	No BC							
all	0.276	0.080	0.022	-4.205	0.055	0.005	0.005	0.266
male	0.268	0.080	0.014	-4.514	0.059	0.004	0.003	0.192
female	0.302	0.074	0.034	-3.783	0.051	0.007	0.006	0.328
white	0.326	0.069	0.042	-3.478	0.049	0.006	0.005	0.122
black	0.248	0.091	0.017	-4.449	0.055	0.006	0.005	0.354
	BC							
all	0.292	0.084	0.021	-3.890	0.052	0.006	0.004	0.124
male	0.279	0.090	0.013	-4.045	0.053	0.005	0.003	0.036
female	0.306	0.077	0.033	-3.676	0.050	0.008	0.006	0.232
white	0.320	0.074	0.042	-3.449	0.048	0.007	0.004	0.051
black	0.227	0.105	0.017	-4.392	0.052	0.007	0.005	0.179
			Higher Risk Aversion					
	No BC							
all	0.302	0.089	0.021	-3.636	0.049	0.006	0.005	0.080
male	0.294	0.080	0.013	-4.091	0.055	0.004	0.003	0.091
female	0.334	0.085	0.030	-3.264	0.046	0.008	0.006	0.093
white	0.347	0.075	0.039	-3.185	0.046	0.006	0.005	0.070
black	0.275	0.095	0.017	-3.988	0.052	0.006	0.005	0.284
	BC							
all	0.307	0.086	0.021	-3.647	0.050	0.006	0.005	0.080
male	0.286	0.085	0.013	-4.100	0.054	0.004	0.003	0.077
female	0.334	0.083	0.029	-3.297	0.047	0.008	0.006	0.095
white	0.353	0.070	0.041	-3.206	0.047	0.006	0.004	0.081
black	0.281	0.095	0.016	-3.889	0.051	0.006	0.005	0.280
			Higher Cost of Education					
	No BC							
all	0.278	0.080	0.023	-4.180	0.055	0.006	0.005	0.256
male	0.274	0.076	0.013	-4.515	0.059	0.004	0.003	0.187
female	0.306	0.073	0.033	-3.770	0.051	0.007	0.006	0.317
white	0.327	0.069	0.042	-3.474	0.049	0.006	0.005	0.116
black	0.248	0.092	0.017	-4.430	0.055	0.006	0.005	0.349
	BC							
all	0.292	0.084	0.022	-3.877	0.052	0.006	0.004	0.120
male	0.277	0.091	0.013	-4.040	0.053	0.005	0.003	0.032
female	0.303	0.078	0.032	-3.717	0.050	0.008	0.006	0.225
white	0.321	0.074	0.042	-3.438	0.048	0.007	0.004	0.050
black	0.228	0.105	0.017	-4.377	0.052	0.007	0.005	0.174
			Diagonal Weighting Matrix					
	No BC							
all	0.309	0.075	0.040	-3.582	0.049	0.007	0.006	145.992
male	0.278	0.080	0.022	-4.173	0.055	0.004	0.003	63.619
female	0.346	0.062	0.046	-3.332	0.048	0.009	0.008	164.601
white	0.372	0.053	0.050	-3.179	0.049	0.008	0.006	63.922
black	0.224	0.107	0.022	-4.315	0.051	0.003	0.004	108.738
	BC							
all	0.320	0.080	0.034	-3.477	0.048	0.006	0.005	74.605
male	0.285	0.091	0.017	-3.905	0.051	0.005	0.003	12.927
female	0.354	0.062	0.045	-3.261	0.048	0.009	0.007	134.302
white	0.374	0.053	0.047	-3.186	0.049	0.008	0.005	51.655
black	0.212	0.114	0.020	-4.310	0.050	0.006	0.004	69.049

This table reports moments for alternative values of calibrated parameters. For the "higher risk aversion" case, the curvature of the CRRA utility function is set at 2. For the "Higher Cost of Education" case, tuition is 20% higher than the baseline. The "Diagonal Weighting Matrix" cases uses the inverse of the variances of the moments as a weighting matrix. These moments are for the cases without and with a borrowing constraint.

Table 23: Elasticities of Moments

parameter	college	under-match	over-match	α_0	α_1	ν_1	ν_2
	All						
all	-0.893	1.830	-0.320	0.127	-0.334	-2.163	-2.387
	0.673	0.684	7.297	-1.930	-1.860	0.087	1.303
	0.000	0.000	0.004	-0.002	-0.002	0.000	0.000
	2.362	-1.356	10.131	-3.836	-2.923	2.181	3.463
	0.292	-0.150	-0.280	0.003	0.160	0.080	0.199
	Male						
	-0.879	1.900	-0.669	0.170	-0.284	-1.623	-1.684
	0.674	0.602	6.653	-1.881	-1.781	0.019	0.929
	0.000	0.000	-0.016	-0.000	-0.000	-0.000	0.000
	2.989	-1.859	12.453	-5.623	-4.274	2.040	3.032
	0.566	-0.315	-0.361	-0.149	0.147	0.129	0.290
	Female						
	-0.888	1.583	0.395	0.042	-0.421	-2.654	-2.897
	0.680	0.800	8.352	-2.008	-1.976	0.033	1.594
	0.000	-0.000	0.004	-0.000	-0.000	-0.000	-0.000
	1.922	-1.102	8.522	-2.001	-1.338	2.217	3.113
	0.269	-0.102	6.216	-0.463	-0.434	0.205	0.703
	White						
	-0.893	1.629	0.560	0.021	-0.440	-2.072	-2.150
	0.674	0.821	9.005	-1.863	-1.855	-0.135	1.093
	0.000	0.001	0.004	-0.001	-0.002	-0.000	-0.000
	2.762	-1.580	11.175	-3.938	-2.886	2.240	3.300
	0.227	-0.183	1.056	-0.188	-0.112	0.099	0.278
	Black						
	-0.801	1.398	-0.212	0.143	-0.295	-3.076	-3.009
	0.801	0.581	8.080	-2.773	-2.519	0.263	2.552
	0.000	0.000	0.005	-0.000	-0.000	0.000	0.000
	1.200	-0.573	6.631	-2.264	-1.744	1.947	3.103
	0.034	-0.030	0.168	-0.043	-0.028	0.027	0.083

This table reports elasticities of moments with respect to parameters for the baseline model with borrowing constraints for the pooled sample.

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