Is College Worth It For Me?

Beliefs, Access to Funding, and Inequality in Higher Education

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Abstract

In the US, the bachelor's attainment rate of high socioeconomic status White youth is much higher than that of Hispanic, Black, and low-socioeconomic status youth. This is true even among students with high academic scores. For high-scorers, how much of these gaps in bachelor's attainment can be explained by differences in subjective beliefs about own academic ability? Relatedly, is targeting information and funding to low socioeconomic status high-scorers more efficient at narrowing overall bachelor's attainment gaps than universal policies like free college for all, or a tracking system in the US? To answer these questions, I estimate the distribution of subjective prior beliefs about own ability using self reported beliefs about college outcomes from the NLSY97 and a dynamic discrete choice model with heterogeneous financial support and beliefs about ability. I find that for Hispanic and low socioeconomic status youth, differences in beliefs explain 38-49% of the gap relative to high-socioeconomic status White high-scorers. However, for Black high-scorers beliefs play almost no statistically significant role in explaining gaps. In the policy analysis I show that the targeted policy is the most efficient at closing gaps and that it closes overall gaps in bachelor's attainment by 25% to 42%, depending on the comparison group. Although targeting information and funding to low socioeconomic status high scorers narrows gaps, inequality will persist with differences in early human capital.

1 Introduction

In the United States there are still large gaps in bachelor's attainment by race, ethnicity, and socioeconomic status (SES). Even among students with high academic ability, youth from lower socioeconomic backgrounds are less likely to enroll in four-year institutions and selective colleges (Hoxby and Avery 2013). Empirical evidence suggest that an explanation for this is that information frictions lead to underinvestment in education for high ability youth from demographic groups where adults are less likely to have college experience (Hoxby and Turner 2013). Specifically, because the whole college experience might be less familiar to these youth they may have less information about their college ability and expected returns than their more affluent peers with similar measures of academic ability.

This paper focuses on differences in bachelor's attainment rates by demographic group. My first question focuses on youth with high measures of academic ability and good behavior, which will be referred to as "High-Scorers." I ask, how do differences in beliefs about own college ability affect inequality in bachelor's attainment rates for high-scorers? This question is important to answer because if information frictions lead to underinvestment of high scorers from disadvantaged backgrounds than there could be serious economic costs, such as foregone earnings or even foregone growth (Hsieh, Hurst, Jones, and Klenow 2020).

My second question is a policy question focused on narrowing overall inequality regardless of being a high-scorer or not. I ask, are policies that target low-SES high-scorers with information and funding more efficient at decreasing overall inequality than policies that are universally applied to all, like free college for all or a tracking policy? The targeted policy can be likened to college recruiting efforts like those studied in Dynarski, Michelmore, Libassi, and Owen 2019 or information campaigns as in Hoxby and Turner 2013.

The measure of inequality used is the difference in bachelor's attainment rates between a given demographic group of interest and high-SES White youth. In this paper the three demographic groups I focus on are low-SES youth regardless of race, as well as Black and Hispanic youth regardless of SES. The efficiency measure used to evaluate the policies is college mismatch. Mismatch is the amount of youth who would make different education decisions if they had complete knowledge about ability. This takes the form of over-investment of low-scoring youth, and under-investment of high-scoring youth in education.

In answer to the first question, I find that differences in beliefs explain 38 percent of the low-SES high-scorer gap, and 49 percent of the Hispanic high-scorer gap. For Black high-scorers, differences in beliefs explains 33% of the high-scorer gap. However, I am unable to rule out an effect of zero for Black high-scorers. The lower effect of Black high-scorers is due to the fact that Black high scorer beliefs are similar to high-SES White high-scorers beliefs. Additionally, I find that for all three comparison groups, differences in financial assistance play important roles in inequality relative to the reference group.

For the policy question, I find that the targeted policy, providing information and funding to low-SES high scorers, is the most efficient policy at reducing inequality. This is because it is the most effective policy in reducing bachelor's attainment gaps, with reductions ranging between 25-42% depending on demographic group[1]. The targeted policy also decreases mismatch by encouraging more education investment from high-scorers. Free college for all also decreases inequality but increases mismatch, since bachelor's attainment rates increase primarily among low-scorers due to low scorers excess optimism relative to the their actual ability. Although the tracking system reduces mismatch, it increases inequality. This is because the increases in bachelor's attainment among high-scorers are offset by decreases in bachelor's attainment from low-scorers for the groups of interest.

To answer these questions, I estimate a dynamic discrete choice model with credit constraints, heterogeneous financial support, and heterogeneous beliefs about ability. The model includes two latent ability types, for low and high-scorers, as well as learning about

[1] It reduces the Black gap by 25%, Hispanic gap by 28.3%, and the low-SES gap by 41.8%

type through GPA. To estimate the model, I use the National Longitudinal Study of Youth 1997, which contains information on earnings, education outcomes, self reported beliefs, financial assistance, and demographic information for youth born in the early 1980s. The data set is particularly useful for this exercise since it over samples Black and Hispanic youth.

The crucial objects of interest are the proportion of high scorers by demographic group, and the distribution of beliefs about ability type. The proportion of high scorers is estimated outside of the model using a finite mixture model with two latent types governing earnings, grades, and human capital measures. The distribution of beliefs is estimated with the model parameters via indirect inference and is identified by two main moments in the data. These are the coefficient from self reported beliefs about college outcomes regressed on enrollment, and the coefficients from grade categories regressed on college exit, both hold financial assistance and demographics constant[2]. Estimating beliefs in this way allows beliefs to not be restricted to equal rational priors that match the ability distributions estimated from the data. It also allows the distribution of beliefs to differ by demographic group based off of model behavior.

Overall once the model, beliefs, and high scorer types are estimated, the results of the policy analysis suggest that targeting information and funding to low-SES high scorers can efficiently increase representation in higher education among Black, Hispanic, and low-SES youth. However, gaps are not completely closed. This is because differences in early childhood human capital investment remain important in explaining differences in bachelor's attainment rates by demographic group.

[2] For an example in the context of occupation choice for how belief paramaters are identified by exit/switching behavior see Papageorgiou and Lopes De-Melo 2016.

1.1 Contribution to the Literature

This paper will contribute to the structural modeling literature that focuses on the role of information frictions in higher education decisions. One strand of the literature uses nationally representative panel data to study the role of information frictions in the decision to enter the high-skilled workforce by going to college (Navarro and Zhou 2017; Cunha, Heckman, and Navarro 2005[3]). The second strand of the literature uses panel data from a single university that includes subjective beliefs along with grades to study the roll of belief formation on dropout and major choice (Arcidiacono, Hotz, and Kang 2012; Stinebrickner and Stinebrickner 2014; Wiswall and Zafar 2015; Reuben, Wiswall, and Zafar 2015).

This paper is closest to Arcidiacono, Aucejo, Maurel, and Ransom 2016. Like this paper I bridge the two strands of the literature together by examining enrollment, non-continuation, bachelor's attainment, and efficiency in the presence of information frictions. However,the main innovation of this paper is that it is the first to combine data on self-reported beliefs about higher education outcomes and predicted model behavior to estimate the distribution of prior subjective beliefs about ability. This is opposed to other papers that set priors to the estimated ability distribution in the data. Because of this beliefs are also allowed to be heterogeneous by demographic background. There is also room for beliefs to be too optimistic or too pessimistic relative to rational expectations estimated from the data. This is what allows me to estimate the role that differences in beliefs play in generating inequality in higher education outcomes. It also allows me to more accurately measure the effect of providing information on bachelor's attainment rates, since under a rational expectations prior this variation may be captured by unobserved preference shocks.

This paper also contributes to the empirical literature demonstrating that information campaigns can increase enrollment and completion for high achieving students from lower

[3]These papers estimate information sets by conducting factor analysis on the error terms of wage regressions along with regressing education choices on factors to test if factors were known at the time of the decision.

income backgrounds. (Dynarski, Libassi, Michelmore, Owen 2020; Hoxby and Turner 2013; Bettinger Long, Oreopoulos, and Sanbonmatsu 2012). The results of my policy analysis not only validate the findings of these papers but also show that if the policies studied in these papers were enacted at the national level, then they can increase representation in higher education as well as decrease mismatch across the United States. In fact these policies can be more effective and generate less inefficiencies than free college for all.

2 Empirical Analysis and Facts

Before discussing the model, this section will show that in the data subjective beliefs are highly correlated with probability of college enrollment, continuation, and completion while holding human capital and financial resources constant. Segments of this empirical analysis will inform the structural model. Specifically, the relationship between education outcomes and belief measures, financial assistance, and grades, will be used as moments to identify model parameters.

2.1 Data

The dataset used in this analysis is the 1997 wave of the National Longitudinal Study of Youth (NLSY97). The NLSY97 is a nationally representative longitudinal data set of individuals born between 1980-1984 living in the United States. The survey was administered annually from 1997 to 2011 and then biannually from there forward. The survey also over samples Black and Hispanic youth in the US. This makes the NLSY97 useful for studying racial and ethnic inequality.

For this paper I use data on parental education, household net worth, self reported probabilities of school enrollment and obtaining a degree by age 30[4], labor market earnings,

[4]For individuals that are missing Probability of Degree, I impute it using the quantitative model equivalent

schooling activities, financial assistance, and parental transfers. Additionally I use demographic information like race, ethnicity, census region, urban/rural categorical variables, gender, as well as year of birth.

I use measures of cognitive human capital and non-cognitive human capital to in the empirical and quantitative analysis to control for early childhood human capital stock (Heckman and Kautz 2014). I use Armed Services Vocational Aptitude Battery (ASVAB) math and verbal scores as measures of cognitive human capital. I also control for non-cognitive human capital by using indicator variables for participation in adverse behavior such as theft, violence, and sexual intercourse before age 15 (Hai and Heckman 2017).

For the empirical analysis and the structural model estimation that follows, the sample is restricted to adolescents who are not missing household net worth, parental education information, earnings in later years, ASVAB test scores, self reported beliefs before age 18 and self reported adverse behavior. For grades I use transcript data in the NLSY97 for GPA, as opposed to the self reported data. I impute transcript GPA for individuals that are missing GPA information from their college transcripts. I do this by regressing transcript GPA on self reported college GPA, demographic characteristics, and human capital measures. I then use the predicted transcript values from the portion of the sample that only includes self-reported GPA.

I drop individuals that identify as Asian, Native American and races marked as other due to small sample sizes. For this reason I restrict the analysis to Hispanic, White, and Black youth. In total the sample size is 2,133 individuals. All statistics, regressions, and patterns in the empirical analysis are weighted using sampling weights created by the Bureau of Labor Statistics for the NLSY97[5].

to probability of degree; probability of enrollment times probability of continuation; using consecutive year estimates of probability of enrollment.

[5]The custom sampling weights for whether individuals are in all years of the sample is used

2.2 Empirical Facts

In this section I review some empirical facts in the NLSY97. Summary statistics by parental education and by race are reported in Appendix A.1 under Table 11 and Table 12. The summary statistics in the appendix show that Black, Hispanic, and lower education background youth have low enrollment and bachelor's attainment rates. They also have less access to resources measured by household net worth, and family financial aid in college. They have lower measures of human capital, as well as more pessimistic beliefs.

In Table 1 I control for parental education, race, ethnicity, access to financial resources, and measured human capital, to see if self reported belief of having a degree is positively related to enrollment, continuation, and bachelor's attainment. Table 1 shows that holding all else constant that being more optimistic is associated with a higher likelihood of enrollment, continuation, and bachelor's degree attainment. This relationship continues to hold in Column 3 even with the inclusion of GPA, and financial assistance from schools, government and family.

We can also see that holding all else constant, being Black and Hispanic are associated with higher enrollment. Additionally, holding all else constant being Black is associated with higher degree attainment and completion conditional on enrollment. This is despite the fact that there are large unconditional gaps in enrollment, completion, and bachelor's attainment by race and ethnicity. Unconditional gaps can be explained by differences in parental wealth and education, as well as human capital measures as shown in Table 11 and 15 in appendix A.1[6].

In Table 2, we examine the relationship between beliefs and demographic characteristics holding human capital constant [7]. Table 2 shows that parental education and household

[6] In Tables 15-16 in appendix A.1, a Oaxaca Blinder decomposition shows that the unconditional gap in enrollment and completion for Black and Hispanic youth is explained in large part due to differences in parental education, household net worth, and measures of human capital. For Hispanics probability of degree is also important.

[7] Sample size differences in Table 2, is due to the fact that the probability of degree question was only

net worth holding all else constant are associated with more optimism. Number of peers with college plans is also positively associated with more optimism. This is consistent with the findings of Hoxby and Avery 2013 and Hoxby and Turner 2013. Their findings suggests that low-SES youth may know less about suitability for college resulting from less adults in their social networks that have higher education experience and less peers that go to college.

Similar to the last specification being Black or Hispanic is associated with more optimism regarding enrollment. Being Black is associated with more optimism regarding completion in addition to enrollment. This suggests for Black youth, beliefs may have little explanatory role for lower bachelor's attainment gaps[8].

Early human capital investments may still play an important role in generating non continuation differences. This is because differences in human capital investment would lead to differences in probability of achieving higher grades in college. Differences in non continuation rates between youth with similar grades however suggests mechanisms other than human capital differences. Figure 1 and Table 3 take a closer look at college non-completion rates holding grades constant. This is measured by students who enroll and do not complete a 4 year degree. This includes those that enroll in community college and exit upon receiving an associates degree[9].

Figure 1 shows not only does non continuation decrease with higher grades, but that this exit behavior in reaction to grades differs by parental education and belief categories concerning probability of bachelor's attainment[10]. In Table 3 we control for measures of hu-

asked to the older cohort, and probability of enrollement was asked for the younger cohorts while in high school. For Table 1 and the quantitative analysis a measure of probability of degree is used that is imputed from subsequent years self reported beliefs of being in school during college age. Any bias in the imputed variable is controlled by the year of birth dummies in Table 1.

[8]Table 14 in Appendix A.1 shows Oaxaca Blinder decomposition results for beliefs. The analysis shows that the unconditional gap for blacks is primarily explained by parental education, hh net worth, ASVAB and peers. This is true for Hispanics too, but there is an unexplained portion coming from the effect of parental education on beliefs. This suggests there are other unexplained reasons for pessimism among Hispanics

[9]Those enrolled in 2 year degree programs are included because they have the option to transfer credits to a four year university. Also according to Hoxby and Avery 2012 it is not obvious that this is always the cheapest option for college.

[10]Beliefs were broken into three categories by setting quantiles for beliefs. 4 quantiles were used but since

man capital and financial resources and still find statistically significant coefficients for belief about bachelor's attainment interacted with GPA category. Similarly, parental education is still marginally significant when interacted with GPA category for high grades, and so is belief about bachelor's attainment interacted with high grades.

The decrease in non-continuation with higher grades, as well as the different effects of grades by belief levels is consistent with the hypothesis that agents don't know their individual returns to college and learn through grades. According to Figure 1 and Table 3 low grades are a strong signal for low returns[11], and high grades are a strong signal for high returns[12]. More optimism might matter more for the medium grades here since the signal is more ambiguous here.

This means that at least for a prior belief not equal to zero or one, low grades may lead to downward adjustments in college returns and more exit, while high grades may lead to high adjustments in college returns leading to more persistence and continuation. Since medium grades provide a less salient signal, beliefs about returns depend more on the prior and hence the marginal effect of beliefs on estimated returns and drop out is stronger. This is consistent with the belief coefficient estimates in Table 3. Another implication of all of the coefficients on grades and the belief variable in Table 3 is that as an agent becomes more optimistic the difference in exit behavior between high and medium grades narrows. For example at a self reported belief of zero, getting high grades as opposed to medium grades leads to a 9 percentage points increase in probability of completion while at a belief of one to only a 1.6 percentage point increase in probability of completion. This is consistent with Bayesian learnings models were optimistic youth near certain of their type not sufficiently adjusting their estimates downwards with bad signals, and hence exhibiting more persistence.

This will be consistent with the belief mechanism introduced later in the quantita-

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there was a lot of bunching 1 group contains two quantiles

[11]Which explains the positive, albeit not statistiaclly significant, stand alone coefficient for beliefs.

[12]Given by the marginally significant stand alone positive coefficient for high grades

tive model. In the model students begin with an original prior estimate of their ability and update with information revealed through grades. If higher ability means more utility from college because of higher post college earnings, then more optimism should lead to higher probabilities of enrollment, as in Table 1. If after grade revelation the new belief is proportional to the prior[13] than receiving the medium grades but having a lower prior estimate means that your new belief would be lower, as in Table 3. Hence continuation probability would be weakly lower for more pessimistic youth with the same grade realization. The rate of decrease also appears to be different by parental education, consistent with the hypothesis that exposure to college through parent's or other influential adult's experiences affects students own ratings of their own ability to succeed in college. This means that the mapping between beliefs about own ability and beliefs about college outcomes may differ by parental education. In the quantitative model estimated beliefs about ability will have an extra effect for parental education to account for this.

2.3 Discussion and Summary of Empirical Facts

We can summarize the findings from the last section as follows. In the NLSY97 we have

1. Holding human capital, race, ethnicity, parental background, access to financial resources constant, youth who are more optimistic about college completion are more likely to enroll, more likely to continue by grade level, and hence more likely to obtain a bachelor's degree.

2. Holding human capital constant, youth from households with more wealth and education are more optimistic about college outcomes.

3. Holding human capital constant, Black and Hispanic youth are more optimistic regarding college outcomes than similar White youth. However there is a larger unconditional

[13] As would be using Bayes Rule

difference in beliefs between Hispanic and White youth[14], than for Black and White youth [15].

What this means is that we find evidence of a connection between subjective beliefs and college outcomes like enrollment, continuation, and degree attainment. Differences in human capital, subjective beliefs, and access to financial assistance by demographic group likely play a role in generating inequality in higher education outcomes as well.[16]

When compared to comparable White youth, Black youth are more optimistic, and have better enrollment and completion rates. For Hispanic youth, relative to White youth, the story is slightly different. They are more optimistic regarding enrollment, and tend to enroll more than similar White students, but this is not the case with respect to college completion. The difference between Black and Hispanic youth in outcomes may be due to more optimism among Black youth, as well as higher levels of government and institutional financial aid[17]. Part of the differences in outcomes may also be due to Hispanic youth comprising a much larger portion of the students from the lowest education backgrounds, while Black youth have parents with slightly better education levels than Hispanics. This is suggested by summary statistic Table 11 and Oaxaca Blinder decompostion in Table 14-16 in appendix A.1.

The positive coefficient for Black youth on beliefs may also mean that information frictions may be less relevant for black youth then other demographic groups. In section 5, we will revisit to what extent beliefs explain different bachelor's attainment rates for high-scoring youth by demographic group.

In the section that follows I will propose a theoretical model that will be calibrated to

[14]See Table 11 in Appendix A.1, where White youth are still more optimistic on average than Black and Hispanic youth

[15]See footnote 11

[16]As shown in Figure 16 appendix A.1. there is little evidence of differences in lower returns to college for Black, Hispanic, low familial wealth, and low parental education youth in the sample.

[17]As suggested by Table 11 and Table 13 in appendix A.1

match moments from the NLSY97 to show how differences in beliefs, along with differences in human capital, financial assistance, and non-pecuniary utility generate higher education decisions and inequality in education outcomes. Once the model is calibrated I will also discuss to what extent there is mismatch in the higher education market and whether any of the three policies that will be discussed can decrease inequality without generating more mismatch.

3 Economic Model

In this section I will propose an economic model that serves two purposes. The first is to demonstrate how differences in beliefs, differences in net tuition (tuition net of financial aid and family assistance), and early human capital development generates inequality in higher education outcomes by race, ethnicity, and parental education. Parameters of the economic model will also be be used to examine the role of beliefs in generating inequality by demographic group and the effects of policies on mismatch and inequality. The model predicts that lower net tuition as well as more optimism regarding latent college ability will have higher levels of enrollment, persistence, and completion, holding all else constant.

The economic environment will consists of agents who live $T = 24$ periods, where each period lasts 2 years and represents an age span from 18-66. This time frame coincides with the end of post secondary education up until retirement. In each period agents can save or borrow up to a specified borrowing limit. While working agents face the natural borrowing limit, but when agents are in school they face a more constrained borrowing limit. The 24 periods will be broken up into 3 stages; enrollment stage, continuation stage, and working stage. Since the worker's problem acts as an absorbing state, the education problem is essentially a two stage problem. This is because in this model once an agent chooses to work they do not return to school.

In the final work stage of the problem, post college earnings, $w_c(\tau_i)$, and non-pecuniary utility, $\mu_c(\tau_i)$, depend on an unknown type $\tau_i \in \{\tau_h, \tau_l\}$ for high-scorers and low-scorers. Where i subscript refers to agent i. The realization of τ_i depends on true probability $P_{\text{true},i}$ of being type τ_h. $P_{\text{true},i}$ depends on parental education, household net worth, race, ethnicity, sex, and measures of human capital. $P_{\text{true},i}$ will capture the positive relationship between early childhood human capital investment, educational attainment, and post college earnings. Since $P_{\text{true},i}$ also depends on demographics it can include a role for labor market discrimination as well.

In the model agents will not know $P_{\text{true},i}$ but they will have a subjective belief P_i. They then update P_i after receiving grades in college as in Stinebrickner & Stinebrickner 2012. P_i captures a broad belief about success at college for the individual, since the latent college ability type generates grades, earnings, and non-pecuniary utility from school.

A decision tree representation of the problem is shown in Figure 2. In the first stage at around age 18 agents have subjective belief P_i, asset level $b_{1,i}$, non-pecuniary utility shocks for work and school, $\vec{\varepsilon}_{1,i} = (\varepsilon_{c,1,i}, \varepsilon_{w,1,i})$.

Agents choose between enrolling in college where they pay net tuition fee $f_{1,i} = tuit_1 - Aid_{GC,i} - Aid_{Fam,i}$, or work and earn non college earnings w_n. Notice $f_{1,i}$ is equal to the sticker price $tuit_1$, net of aid from government or college $Aid_{GC,i}$ and families $Aid_{Fam,i}$.

In the second stage at around age 20 agents realize a signal for their latent type given by the GPA g_i for the previous schooling period. They then update P_i to $P'(P_i, g_i)$, and observe non-pecuniary utility shocks for school and work, $\vec{\varepsilon}_{2,i} = (\varepsilon_{c,2,i}, \varepsilon_{w,2,i})$. They then decide to continue schooling and pay net tuition $f_{2,i} = tuit_2 - Aid_{GC,i} - Aid_{Fam,i}$, or dropout to work and earn w_s for having completed some college. Like $f_{1,i}$, $f_{2,i}$ is the sticker price $tuit_2$ in period 2 net of aid from government or college $Aid_{GC,i}$ and families $Aid_{Fam,i}$. Government, college and family aid are assumed to be equal for period 1 and 2, while sticker price is allowed to be different.

If agents choose to complete school then after the next period from ages 22-66 agents work and earn earnings dependent on type, $w_c(\tau_i)$ each year as well as non monetary utility $\mu(\tau_i)$. Agents make borrowing saving decisions in all periods of the problem whether in school or in the labor force. During School the borrowing limit is $-B_s(t)$ while in the labor force it is $-B_n(w)$, with $-B_s(t) \geq -B_n(w)$ so that credit constraints are more binding while enrolled in school (Lochner and Monge-Naranjo 2012).

Heterogeneity by parental background, race, and ethnicity enters the problem through four channels. The first is through the distribution of initial subjective beliefs P_i. Second through transfers from parents, government, and institutions that lead to differences in net tuition $f_{t,i}$ for $t = 1, 2$ while in school. Third through the true probability of being type τ_h, $P_{\text{true},i}$ which determines the distribution of grade realizations and future earnings. Finally through the distribution of non-pecuniary utility shocks $\vec{\varepsilon}_{t,i}$.

In order to allow for human capital development while in school, mean earnings are such that $w_n < w_s \leq w_c(\tau_i)$ reflecting increasing mean returns to years of schooling regardless of type. Even though expected earnings increase with schooling, a binding credit constraint while in school will make college much less appealing for those with $\tau_i = \tau_l$. This is because agents will be unable to consumption smooth and face lower consumption for the first two periods of their life.

3.1 Workers Problem

At any time period t, for all three stages the workers problem is given by (1) below. Where utility depends on, assets/debt b_i, earnings w, and t since this determines how many periods agents have left in their life cycle.

$$(1) \qquad V_w(w, b_i, t) = \max_{\{b_{n,i} \geq -\tilde{B}_n(w)\}_{n=t}^{T}} \sum_{n=t}^{T} \beta^{n-t} u(w + Rb_{n,i} - b_{n+1,i})$$

Per period utility $u(\cdot)$ is given by CRRA preferences of the form

$$(2) \qquad u(c_i) = \frac{c_i^{1-\gamma} - 1}{1-\gamma}$$

For every period the borrowing constraint is the natural borrowing limit, given below. The natural borrowing constraint is determined by how much the agent can credibly pay back in the future. As a result in the final period T, agents are not allowed to borrow.

$$\tilde{B}_{T-n}(w) = \frac{w + \tilde{B}_{T-n+1}(w)}{1+r} \qquad \tilde{B}_T = 0$$

Therefore in the final period $b_{T+1} = 0$.

3.2 Enrollment Work Problem

In the first stage, corresponding to age 18, agents make the decision to enroll in school or work starting at period one until the end of the life cycle. Agents begin with initial assets $b_{1,i}$, unobserved tastes for college and work $\vec{\varepsilon}_{1,i} = (\varepsilon_{c,1,i}, \varepsilon_{w,1,i})$ a belief P_i that they are of type τ_h. The agent's stage 1 problem is thus given by (3) below.

$$(3) \qquad V_1(P_i, b_{1,i}, f_{1,i}, \vec{\varepsilon}_{1,i}) = \max\{V_w(w_n, b_{1,i}, 1) + \varepsilon_{w,1,i}, V_{c,1}(P_i, f_{1,i}, b_{1,i}) + \varepsilon_{c,1,i}\}$$

$$s.t.$$

$$V_{c,1}(P_i, f_{1,i}, b_{1,i}) = \max_{b_{2,i} \geq -\tilde{B}_{s,1}} [u(Rb_{1,i} - f_{1,i} - b_{2,i}) + \beta \mathbb{E}_{g,\varepsilon}(V_2(P'(g, P_i), f_{2,i}, b_{2,i}, \vec{\varepsilon}_{2,i})) \; |P_i \;]$$

Agents update beliefs after realizing grades using Bayes Rule according to equation (4), where the new belief $P'(g, P_i)$ is given below. Where $\pi_{k,j} = Prob(g_k | \tau = \tau_j)$.

$$(4) \quad P'(g_k, P_i) = \frac{P_i \pi_{k,h}}{P_i \pi_{k,h} + (1 - P_i)\pi_{k,l}}$$

3.3 Completion Dropout problem

In the second stage, corresponding to age 20, agents make the decision to continue and complete college or dropout and work for the remainder of the life cycle. Agents observe GPA g from the first stage then update belief P_i to $P'(g, P_i) = P'_i$. Agents also begin the second stage with debt/savings from the first stage $b_{2,i}$, and realize unobserved tastes for college and work $\vec{\varepsilon}_{2,i} = (\varepsilon_{c,2,i}, \varepsilon_{w,2})$ respectively. The agent's problem is given by

$$(5) \quad V_2(P'_i, f_{2,i}, b_{2,i}, \vec{\varepsilon}_{2,i}) = \max\{V_w(w_s, b_{2,i}, 2) + \varepsilon_{w,2,i}, V_{c,2}(P'_i, f_{2,i}, b_{2,i}) + \epsilon_{c,2,i}\}$$

$$s.t.$$

$$V_{c,2}(P'_i, f_{2,i}, b_{2,i}) = \max_{b_{3,i} \geq -\tilde{B}_{s,2}} [u(Rb_{2,i} - f_{2,i} - b_{3,i}) + \beta(P'_i[V_w(w_c(\tau_h), b_{3,i}) + \mu_c(\tau_h)]$$
$$+ (1 - P'_i)[V_w(w_c(\tau_l), b_{3,i}) + \mu_c(\tau_l)]) \quad]$$

Grades reveal information about τ_i since their distribution depends on τ_i. But since τ_i also determines non-pecuniary utility, the information revealed in school can also include psychosocial elements of higher education that are often discussed in the sociology literature. In this model, the assumption is that this is closely tied to performance, and a bad signal in performance will likely reinforce that college will not be a good fit for the individual. Factors that are likely to be more stable between the first and second period such as distance from home community, enjoyment of school, and family obligations would be captured through a constant location parameter of non-pecuniary shocks $\vec{\varepsilon}_{t,i}$. The location parameter will be allowed to differ by demographic group.

Since in the first two stages the agent faces a discrete choice problem, the optimal decision for each agent can be described by a cutoff rule with respect to belief about type. Where if P_i is higher than a certain threshold the agent will enroll. For example in the first stage the optimal decision could be characterized by equation 6 below, where $\sigma_{d,2}, \mu_{d,2,i}$ are the normalized scale parameter and location parameters[18] for the Type I extreme value shocks.

$$(6) \qquad \text{Choice}_{t=1,i} = \begin{cases} \text{Enroll} \quad \text{if} \quad P_i > \tilde{P}_1(b_{1,i}, f_{1,i}, f_{2,i}, \vec{\varepsilon}_{1,i}, \mu_{d,2,i}, \sigma_{d,2}) \\ \text{Work} \quad \text{if} \quad P_i \leq \tilde{P}_1(b_{1,i}, f_{1,i}, f_{2,i}, \vec{\varepsilon}_{1,i}, \mu_{d,2,i}, \sigma_{d,2}) \end{cases}$$

.

Similarly in stage 2, given $\{\pi_{k,j}\}_{k,j}$ the decision to continue also follows a cutoff rule for updated belief $P'(g_k, P_i)$ after realizing $g_k, \varepsilon_{c,2,i}, \varepsilon_{w,2,i}$ and starting with P_i, given by equation (7) below.

$$(7) \qquad \text{Choice}_{t=2,i} = \begin{cases} \text{Continue} \quad \text{if} \quad P'(g_k, P_i) \geq \tilde{P}_2(b_{2,i}, f_{2,i}, \vec{\varepsilon}_{2,i}) \\ \text{Dropout} \quad \text{if} \quad P'(g_k, P_i) < \tilde{P}_2(b_{2,i}, f_{2,i}, \vec{\varepsilon}_{2,i}) \end{cases}$$

.

The cutoff rules holding non monetary utility shocks and distribution constant, are weakly increasing in $f_{1,i}, f_{2,i}$. In certain spaces of the distribution of non monetary utility shocks the decision rules are strictly increasing in $f_{1,i}, f_{2,i}$. $P'(g_i, P_i)$ also increases in P_i. For $P_i \in (0, 1)$, if higher grades provide a stronger signal of being $\tau_i = \tau_h$, $P'(g_i, P_i)$ will increase in g_i. Therefore depending on the underlying distribution of grades and earnings by type, as well as non monetary utility shocks, the model can reproduce some of the facts discovered in the empirical analysis. Particularly higher levels of financial assistance may allow more

[18] Normalized with respect to the difference in Type I extreme values. Since the difference in shocks is what is identified

pessimistic students to enroll. On the other hand for students with low levels of financial assistance more optimistic initial beliefs along with better grades will allow more students to enroll and complete college.

3.4 Example for Model Prediction

Figures 3, 4, and 5 provide an example for how financial assistance, subjective beliefs of having $\tau_i = \tau_h$, and early childhood human capital investment realized through grades affect probability of enrollment, continuation, and degree attainment in the model.

In Figure 3 we see that more financial assistance through lower net tuition leads to a higher probability of enrollment at all belief levels. Because of the belief cutoff we also see that probability of enrollment is flat and then increases with subjective beliefs at all net tuition levels displayed. This means that if two youth have the same beliefs but different access to resources than probability of enrollment will still be different. Like wise if their access to resources are the same but beliefs differ than probability of enrollment can also differ.

Figure 4 shows conditional on already enrolling, how probability of continuation differs by grade revelation. This shows how learning affects the continuation decision. We can see that high grades which are a signal of being a high-scorer. After a certain belief threshold higher grades lead to an increase in the probability of continuation. The difference in continuation probability between high grades and medium grades diminishes as a youth gets more optimistic [19]. For the same initial belief, lower grades lead to a dramatic decrease in continuation except in the case where the agent is near certain they are a high or low scorer.

Figure 5 takes probability of enrollment and continuation together and shows that even though the effect of net tuition is somewhat more muted than in Figure 3, net tuition and

[19]this is consistent with the standalone and interacted coefficients for GPA category estimated in Table 3

subjective beliefs about being a high-scorer still affect the probability of degree attainment in the model.

Some discussion on the assumptions of the model is warranted. First is the fact that college decisions happen only in the first four years of life. The model can be changed to allow for switching back from work to school, that way later enrollment decisions can be allowed for as well as the saving up of assets for school. The main object of interest will be bachelor's attainment period not so much timing of enrollment. Any bias introduced by ignoring systematic differences in later enrollment would be captured in the non-pecuniary utility components that are allowed to differ by demographic group.

The second objection raised can include the fact that beliefs about probability of acceptance that also depend on τ_i is not included. The model can also be adjusted for this, where probability of acceptance could depend on latent type and agents can learn from acceptance as well. However since in the data we look at any enrollment including at non selective community colleges we do not include it. For these colleges acceptance probability is likely close to one. Even if youth enroll in community college, the possibility still exists to transfer to a four year university.

Finally uncertainty regarding tuition is not explicitly modeled. In the calibration this is indistinguishable from allowing the net tuition rate to change between periods. This is because over estimating tuition and learning it were lower after enrollment would be equivalent to $f_{1,i}$ being higher than $f_{2,i}$. However in the calibration this would be an average uncertainty in tuition not dependent on demographics, which can be adjusted in future formulations. We can also extend the model where second period net tuition depends on latent type, grade realization or human capital measures. For simplicity we will use average tuition by demographic as in Hai and Heckman 2017.

In the next section we will discuss the calibration of the model. The model will then be used to discuss how beliefs, financial assistance, and human capital investment with earnings outcomes affect gaps in educational attainment, with the focus on bachelor's attainment. Then given this role we will discuss the effect that universal free college and targeted college have on inequality and mismatch.

4 Estimation of Quantitative Model

In this section I discuss how I identify and estimate the parameters of the structural model described in section 3. I will also describe some of the assumptions governing the distribution of earnings as well as parameters whose values will be set outside of the estimation routine. I will also discuss what data moments are used to identify parameters related to the main mechanisms of the model.

As section 3 suggested the model will include room for differences by race, ethnicity, and parental background in financial assistance, and non-pecuniary utility. The financial assistance measure used in the model will be the predicted financial assistance given demographic information as in Heckman and Hai 2017. This will be estimated separately for financial assistance that comes from family and for financial assistance that comes from universities or government[20]. In addition to type dependent non-pecuniary utility in the final stage, the distribution of non-pecuniary utility shocks will also depend on race, ethnicity, and whether the student is a potential first generation college student[21]. This is to control for any inherited preferences for college by parental education or for unobserved differences in the college experience for minorities.

The distribution of beliefs will be a linear function of measured beliefs about college completion from the NLSY97 and parental education. Systematic differences by race, ethnicity and socioeconomic status in measured beliefs[22] will allow for systematic differences

[20]Including work study

[21]That is if their parents had ever attended college

[22]Table 2 shows all else equal parental education is positively correlated with optimism regarding degree attainment. Table 11 shows average beliefs differ by race and ethnicity with Hispanics being the most

in the estimated distribution of subjective beliefs. The estimated distribution of subjective beliefs will have an extra effect for parental education to capture information gained through parents education experiences that might not be captured in the measured beliefs. In addition to systematic differences in cognitive and non cognitive measures, the estimation of P_{true} will also allow for an extra effect to come from race, ethnicity and parental background. This can capture unobserved human capital and discrimination in actual outcomes while in school and the labor market.

First I will explain the externally estimated parameters. Then I will explain the moments and parameters that will be estimated using indirect inference with some discussion on how the model is identified.

4.1 External Parameters

The parameters that will be set outside of the model are given in Table 4. The coefficient of relative risk aversion γ, the discount factor β, and the interest rate $(1 + r)$ are set to standardly assumed values. The college borrowing limits are set to match average student debt levels as in Abbot Gallipoli, Meghir, and Violante 2016. The first stage borrowing limit while in school is set to \$16,600 in 2017 dollars. The second period borrowing limit is set to \$31,100. Together these match average borrowing for the first two years and last two years of college respectively (Wei and Skomsvold, 2011). In total the amount students are allowed to borrow in the model is higher than the highest cumulative total that students could borrow from Federal student loan programs for a bachelor's degree, \$46000, which likely reflects the use of private loans amongst some students (Lochner and Monge Naranjo 2010).

Financial assistance is estimated outside of the model. Where financial assistance is the sum of family aid and government/institution financial aid. The distribution of financial assistance is drawn from a log normal distribution, of the form below, estimated by OLS.

pessimistic.

$$(8) \qquad \ln(f_{i,k}) = X_i\beta_{f,k,} + \beta_{f,y}birthyear + \epsilon_{f,k,i}$$

Where X_i includes demographic variables like race, ethnicity, gender, household net worth, parental education, and a constant term. The subscript k indicates that Equation 9 above is estimated separately for family assistance $k = 1$ and government/institution financial assistance $k = 2$. To get total financial assistance, the sum of both predicted values for students is used. Therefore financial assistance used in the model is the predicted value given by demographic and socioeconomic variables (Hai & Heckman 2017).

The distribution of latent type τ by demographic group will be estimated using a finite mixture model (FMM). The latent variable will take two values for $\tau_i \in \{\tau_l, \tau_h\}$, respectively corresponding to low-scorers and high-scorers in the rest of the paper. The effect of being τ_l is normalized to 0. The effect of being τ_h will be estimated through the estimation of the three following measurement equations in the finite mixture model.

$$(9) \qquad Z^*_{i,j} = \alpha_{z,j}1(\tau_i = \tau_h) + \eta_{z,j}X_i + \varepsilon_{z,j} \qquad j \in \{1, \ldots, J_c\}$$

$$(10) \qquad \ln w^*_{i,s} = \mu_{w,0} + \mu_{w,1}1(s \in (12, 16)) + 1(s \geq 16)(\mu_{w,2} + \mu_{w,h}1(\tau_i = \tau_h)) + \varepsilon_{w,s}$$

$$(11) \qquad \pi(g|\tau) = \frac{exp(\gamma_{g,0} + \gamma_{g,\tau}1(\tau_i = \tau_h))}{\sum_{k=l,m,h} exp(\gamma_{k,0} + \gamma_{k,\tau}1(\tau_i = \tau_h))}$$

In equation (9) $Z^*_{i,j}$ are measures of cognitive and non cognitive ability. The measures of cognitive ability are the ASVAB scores for arithmetic reasoning, paragraph comprehension, word knowledge and mathematical knowledge. The non cognitive measures are participation in adverse behavior at young ages; sex before age 15 as well as any violence and any theft greater than \$50 at the start of the survey. To incorporate both binary and continuous variables the specification below for $Z^*_{i,j}$ will be estimated in the FMM. The choice of human capital measurements and specification for $Z_{i,j}$ follows Hai and Heckman 2017.

$$Z_{i,j} = \begin{cases} Z^*_{i,j} & \text{if } Z^*_{i,j} \text{ is continuous} \\ \mathbf{1}(\boldsymbol{Z^*_{i,j}}) & \text{if } \boldsymbol{Z^*_{i,j},} \text{ is binary} \end{cases} \qquad i \in \{c, n\}$$

Log earnings dependent on years of schooling s for individual i are described in equation (10) by $\ln(w_{i,s})$. The variance of the error term is allowed to differ for whether a student has no college experience $s \leq 12$, some college experience $s \in (12, 16)$, or a bachelor's $s \geq 16$.

Additionally the distribution of grades $g \in \{g_l, g_m, g_h\}$ for low ($GPA < 2.0$), medium ($2.0 \leq GPA < 3.0$), and high ($3.0 < GPA$), conditional on τ is estimated using equation (11) above. To describe the distribution of grades by demographic type, the distribution of type by demographic is also needed. The distribution of type will also be important for the effect of the policies discussed later in the paper. This is described fully by $P(\tau_h; \vec{X}_i) = Prob(\tau_i = \tau_h | \vec{X}_i)$ in equation 12 below. Since $P(\tau_l; \vec{X}_i) = 1 - \ Prob(\tau_i = \tau_h | \vec{X}_i)$.

$$(12) \qquad P(\tau_h; \vec{X}_i) = Prob(\tau_i = \tau_h | \vec{X}_i) = \frac{exp(\vec{X}_i \vec{\beta}_p)}{1 + exp(\vec{X}_i \vec{\beta}_p)}$$

Using equations (9)-(12), human capital measurements, earnings, and grades from the NLSY97, the FMM can be estimated using the individual likelihood function given by $f(\vec{Z}_i, w_i, g_i; \tau_k, X_i, s)$. The objects of interest are the parameters in (9)-(12). These objects are estimated by solving for the maximum likelihood given below in equation (13). The likelihood equation will control for differences in probability of enrollment and continuation given demographic information as well. For more detailed information regarding the functional form of the likelihood function as well as the parameter results of the individual likelihood function see Appendix A.2-A.3.

$$(13) \qquad \max \quad \sum_i \ln[P(\tau_h; \vec{X}_i) f(\vec{Z}_i, w_i, g_i; \tau_h, X_i, s_i) + (1 - P(\tau_h; \vec{X}_i)) f(\vec{Z}_i, w_i, g_i; \tau_l, X_i, s_i))]$$

Once equation (8), along with the finite mixture model given by equation (9)-(13) are estimated, we use the sum of the predicted financial assistance variables for total financial assistance, predicted earnings from $\ln w_{i,s}$ for $w_n, w_s, w_c(\tau_l), w_c(\tau_h)$[23], and $\pi(g|\tau)$ for the conditional grade probabilities in the model. The individual probability of being a high-scorer that will used for individual $P_{\text{true},i}$ is explained below in equation (14).

$$(14) \qquad P_{\text{true},i} = Prob(\tau_i = \tau_h | \vec{X}_i, \vec{Z}_i, w_i, g_i, s_i) \propto P(\tau_h; \vec{X}_i) \times f(\vec{Z}_i, w_i, g_i; \tau_h, X_i, s)$$

$P_{\text{true},i}$ is therefore the posterior probability of being a high-scorer estimated from the finite mixture model. In this way the distribution of individual grades in college as well as the probability of completing college will depend on the individual early human capital stock given by the vector $\vec{Z}_i$. $P_{\text{true},i}$ will be used to simulate high types and low types in the quantitative model.

In the information policy counterfactuals in section 5 a modified posterior will be used that only takes into account ASVAB scores and behavior indicators. This is to mimic the kind of information that would be available to policy makers or school administrators

[23]Earnings and financial assistance are set to 2017 dollars

prior to college[24].

4.2 Internally Estimated Moments

The remaining moments to be calibrated within the model are the sticker price of tuition $tuit_1$, $tuit_2$, the distribution of subjective beliefs of being type τ_h, the non-pecuniary utility dependent on τ, $\mu_c(\tau_i)$, as well the distribution of preference shocks. The distribution of preference shocks is given by the type I extreme values shocks whose location parameters differ for White, Black, and potential first generation students. The variance for the Type 1 extreme value shocks for the first and second period will also be allowed to differ.

The distribution of subjective beliefs of being high type is given by a truncated normal distribution at zero and one given by equation (15) below.

$$p_i = \gamma_{p,0} + \gamma_{p,b} ProbDegr + \gamma_{p,h} Pedu_{\text{hsg}} + \gamma_{p,s} Pedu_{\text{scol}} + \gamma_{p,b} Pedu_{\text{bach}} + \epsilon_{p,i} \tag{15}$$

The assumption used in equation (14) is that data contained in the variable Prob Degr from the NLSY97, is a noisy measurement of the subjective belief of being type τ_h. The measurement error is allowed to differ by parental education. This is to capture information about college that youth may receive from their parents higher education experiences. A truncated normal is used since we want to allow for 1's and 0's since these are meaningful in the model. Where a value of 1 or 0 means that agents are certain of their type and hence will not change their mind with grades.

The distribution of type 1 extreme value shocks, non-pecuniary utility by type $\mu_c(\tau_i)$ and the parameters in equation (15) will be internally estimated by indirect inference. Standard errors for the parameters will be estimated by bootstrapping. The moments that will

[24] Specifically $Prob(\tau_i = \tau_h | \vec{X}_i, \vec{Z}_i) \propto P(\tau_h; \vec{X}_i) \times f_Z(\vec{Z}_i; \tau_h, X_i)$ will be used.

be targeted in the indirect inference specification are the coefficients for the following two regressions in equation (16) and (17).

$$(16) \quad Enroll = \beta_{E,0} + \beta_{E,B} HighBelief + \beta_{E,F_2} T2(Finaid) + \beta_{E,F_3} T3(Finaid)$$

$$+\beta_{E,1G} FirstGen + \beta_{E,W} White + \beta_{E,H} Hisp + \varepsilon_{E,i}$$

$$(17) \quad Continue = \beta_{C,0} + \beta_{C,G_m} GPA_m + \beta_{C,G_h} GPA_h + \beta_{C,F_2} T2(Finaid) + \beta_{C,F_2} T3(Finaid)$$

$$+\vec{\beta}_{C,PH} Pedu_{\text{hsg}} + \vec{\beta}_{C,PS} Pedu_{\text{scol}} + \vec{\beta}_{C,PB} Pedu_{\text{bach}} + \beta_{C,W} White + \beta_{C,H} Hisp + \varepsilon_{C,i}$$

Where $FirstGen$ is an indicator for being a first generation student, $HighBelief$ is an indicator for being in the top half of belief distribution, $T2(Finaid), T3(Finaid)$ are indicators for being in the 2nd and third terciles of the total financial assistance distribution. For a quick discussion of identification see Table 5.

The specific problem that will be solved is given below, in equation (17). The parameter vector Γ are those parameters that minimize the difference between the simulated regression coefficients and data regression coefficients. $\tilde{\beta}(\Gamma)$ are the simulation coefficients given Γ, while $\vec{\beta}$ are the regression coefficients from the data. W is the weighting matrix given by the inverse of the diagonal matrix of the standard errors of the data regression coefficients.

$$(17) \qquad \min_{\Gamma} (\tilde{\beta}(\Gamma) - \vec{\beta})' W (\tilde{\beta}(\Gamma) - \vec{\beta})$$

Important parameters are reported in Table 7. For the complete list of estimates see Table 22 Appendix A.4. Using the calibrated and preset parameters we can then decompose high-scorer inequality by differences in financial aid, subjective beliefs, and non-pecuniary utility. Overall gaps would also be determined by $P_{true,i}$. We can then evaluate the effects of policies on inequality and mismatch in higher education by race, ethnicity and parental background.

4.3 Identification Discussion

Equations (16) and (17) essentially match the two main stages of the model where education choices are made. This is stage (1), the enrollment vs work choice and stage (2), the continuation vs exit and work stage. The main parameters of interest in this estimation are the distribution of beliefs about type that is given by equation (15). Estimation is aided through the external estimates of earnings by schooling choice and type, as well as the conditional grade probabilities given type.

To aid in understanding, first abstract away from the role of financial assistance, race, ethnicity and parental education in (16), (17), and (15). Beliefs given by p_i only matter to the extent that utility from completing college for high-scorers is greater than utility from completing college for low-scorers, as well as the relative utility of non college and some college. All of these depend on $w_c(\tau), w_s, w_n$, which is externally estimated. The difference in expected utility between school and work is also determined by the mean difference of type I extreme value shocks for school and work, which is assumed to be the same in stage 1 and stage 2 of the problem. The difference in utility from college between low and high types is also determined by $\mu_c(\tau)$.

If the normalized location parameter[25] and $\mu_c(\tau)$ are such that work is always preferred, college is always preferred, or there's no difference in post college utility between high

[25] College minus work type I extreme value shocks

and low scorers, then we would have trouble matching some of the patterns in the data.

The empirical results discussed in section 2 requires that the parameter space is such that beliefs matter. This is primarily through the coefficient on measured beliefs and the effect of grades on enrollment in equations (16-17). The top panel in Figure 6 also shows that grades do provide a signal for type in the finite mixture model. Therefore in the quantitative model there should be an increase in enrollment probability with more optimism as well as a differential response to grades in the continuation stage. This restricts the values of the location parameters and the type dependent non pecuniary utility.

Identification of beliefs depends on two crucial features of the data. One is that enrolling is positively correlated with measured beliefs in the data as captured by $\beta_{E,B}$, controlling for access to resources. The second is the difference in college continuation by GPA category. This is given by β_{C,G_m} and β_{C,G_h}.

If we focus on the enrollment stage and equation (16) $\gamma_{p,b}$ in (15) is primarily identified through $\beta_{E,B}$ in (16). Since this determines how important measured beliefs are in enrollment which enters the model through subjective beliefs about type.

The location of beliefs given through $\gamma_{p,0}$ is identified through difference in response to GPA. Panel 2 in Figure 6 shows that if prior stage 1 beliefs are too optimistic or too pessimistic then there is little change in beliefs. Therefore the degree to which grades affect updating and hence continuation depends on the location of the distribution of the prior. If estimated beliefs are located near the center of $(0, 1)$ then here changes in beliefs will lead to the biggest updates and hence biggest grade response. Therefore $\gamma_{p,0}$ will be set to where this best matches equation (17) from the data.

Responses to financial aid in enrollment and continuation given by $\beta_{E,F_2}, \beta_{E,F_3}, \beta_{C,F_2}, \beta_{C,F_3}$ will identify $tuit_1$ and $tuit_2$. This is because financial assistance is externally estimated and $tuit_1$ and $tuit_2$ will set net tuition rates by demographic group which also play an important role in the higher education decision given by the quantitative model.

Differences in the location parameter by race and ethnicity will be identified through the effect of race and ethnicity in equation (16), given by $\beta_{C,W}, \beta_{C,H}$. The effect of being a first generation college student on the difference in the location parameter is identified through $\beta_{E,1G}$. The effects of parental education on beliefs are identified by $\beta_{C,PH}, \beta_{C,PS}, \beta_{C,PB}$ in equation (17).

The variance on the unobserved portion of belief in equation (15), the period specific scale parameters for the type I extreme values, and the period constant location parameter for the type I extreme value shocks, would help match the levels of enrollment and continuation, as well as create extra variation needed to fit the data. The type dependent non-pecuniary utility, $\mu_c(\tau)$ helps to adjust response to grades if the response implied by the finite mixture model through earnings and $\pi(g_k, j)$ is too restrictive. In total we will have leads 16 parameters that will be estimated by 17 moments.

4.4 External and Internal Estimation results

Table 6 shows the implications on model earnings from the results of the log earnings equations of the finite mixture model. We see that regardless of type, annual earnings increase with education. As expected enrolling and completing school will lead to higher earnings for all youth, regardless of scorer type. However high-scorers have higher earnings than low-scorers upon completing college.

If there were no non-pecuniary utility and credit constraints, then all youth would choose to enroll and complete college. However in the presence of binding credit constraints the lower utility from low consumption for the first two periods may deter some youth from pursuing education. This is especially the case if they believe they will incur some non-pecuniary utility costs from being a low-scorer as well.

Table 7 shows several of the key parameters that were estimated in the internal calibration exercise. The factor loading on probability of degree attainment, is 0.87 with a very precise standard error estimate. This suggest that this variable does capture beliefs about being a high-scorer with $\tau_i = \tau_h$. Holding the measured belief constant as well, the higher education background a youth comes from the more optimistic they are that they are type τ_h. This is consistent with the hypothesis that youth who know more adults with college education will rate their fit for college higher and perhaps closer to the truth if they are high-scorers.

Figures 7-9 provide a quick snapshot of how well the model matches patterns we see in the data. Figure 8 and the left side graph of Figure 7 show that the model slightly underestimates enrollment and non completion. However on balance it has a good fit with regards to BA attainment. As we can see from Figure 9 and the left side of Figure 7, this success at capturing BA attainment carries over when we condition by demographic group as well. The quantitative model matches gender and household net worth bachelor's attainment even though these were not directly targeted in the indirect inference specification. For more information regarding model fit of the indirect inference moments see Appendix A.4.For the results of the finite mixture model and financial assistance estimation see Appendix A.3.

5 Quantitative Results

In this section I will use the estimated quantitative model to answer two questions. The first is, for high scorers, how much of the gap in bachelor's attainment rates relative to high-SES White youth is explained by differences in beliefs and financial assistance? The second question is, will a policy that targets information and funding to high scorers from low-SES backgrounds be more efficient at closing overall bachelor's attainment gaps[26] than universal policies such as free college for all or instituting a tracking system in the United States.

For both questions the main outcome of interest, bachelor's attainment gaps, is de-

[26]gaps independent of scorer type relative to high-SES White youth.

fined as the difference in bachelor's attainment rates between high-SES White youth versus the three comparison groups, Black, Hispanic, and low-SES youth[27]. For the first question inequality is measured within high-scorers only. Where high scorers are those simulated by the model, whose realizations depend on human capital measures, earnings, and grades. For the second question inequality is measured independent of scorer type.

In this section low-SES youth, are those whose household is in the bottom tercile of the net worth distribution or whose parents have a high school diploma or less. High-SES youth are those whose household is from the top tercile of the wealth distribution and whose parents have at least a bachelor's degree.

Before discussing the main results of this paper I will discuss the estimated information frictions and mismatch present in the baseline version of the model.

5.1 Information Frictions and Mismatch

This section will discuss information frictions and mismatch by scorer type, with some discussion on how this differs by demographic group. I will also explain how this mismatch can help us predict the effect of policy on inequality.

In the model subjective beliefs can differ with respect to $P_{\text{true},i}$, which is how much they differ from a rational expectations prior. Subjective beliefs can also differ from the truth, which is the actual type of the agent. Differences relative to $P_{\text{true},i}$ will determine the effects of policy providing more accurate estimates of P_{true} to youth. While differences in beliefs relative to the youth's actual type will affect the measure of efficiency used in this model, mismatch.

In this analysis, mismatch is defined as the percentage of youth who would change their decision to get a bachelor's or not, if they knew their type with complete knowledge.

[27]Black and Hispanic youth includes youth from all socioeconomic backgrounds. Low-SES youth includes youth from all racial and ethnic groups in the sample

This will take the form of under investment among high-scorers and over investment among low-scorers.

Figure 10 shows the difference in mean subjective beliefs vs estimated $P_{\text{true},i}$ by demographic group and scorer type. We see that for Black, Hispanic, low-SES, and high-SES White youth subjective beliefs are on average inaccurate compared to those estimated from the data. High-scorers are too pessimistic and low-scorers are too optimistic on average. On average Black, Hispanic, and low-SES high-scorers know something about their type since their beliefs are more optimistic than low-scorers. For high-SES White youth beliefs are almost the same between low and high-scorers.

High-scorers are also closer to the truth than low-scorers for all demographic groups under consideration. Therefore we should expect that policies revealing estimates of $P_{\text{true},i}$, like tracking and the targeted policy, will have different effects by type. For instance tracking should lead to a bigger readjustment of low-scorers' beliefs than for high-scorers' beliefs. Providing information to everyone can perhaps lead to a bigger decline in bachelor's attainment from low scorers than the increase in bachelor's attainment from high-scorers. Additionally if there are more low scorers than high scorers among Black, Hispanic, or Low SES youth, then this can generate more inequality.

For the targeted policy that provides information only to low-SES high scorers, we should see that it should close gaps. Under this policy we will not see a change in low-scorer's beliefs because they will not be targeted. It should also close gaps the most for low-SES youth. This is because the difference in beliefs with respect to $P_{\text{true},i}$ is larger for low-SES youth than for Black and Hispanic high-scorers. Additionally, Black and Hispanic youth benefit only to the extent that they are also low-SES high scorers.

Figure 10 can also help us predict the effect of for free college for all, a policy that does not address beliefs but reduces net tuition for everyone. Since in figure 10 low-scorers are overly optimistic, we should see that increasing funding to everyone will likely lead more low-scorers to enroll as well as some high scorers. This may increase over investment from low-scorers and perhaps mismatch as well.

Next Figures 11-12 show what education decisions are in the baseline versus what they would be if agent's knew their type with certainty. Hence they show mismatch. The top panel in Figure 11 shows the bachelor's attainment rate of High-scorers in the baseline scenario and under complete information about type by demographic group. The first thing to notice is that there is substantial underinvestment among all high-scorers. However, this is less the case for high-SES White youth.

The bottom panel in Figure 11 shows the bachelor's attainment rate of low-scorers in the baseline scenario and under complete information by demographic group. Conversely there is over investment occurring in the higher education market for low-scorers from all demographic groups. This over investment is highest for high-SES White low-scorers.

Finally the top panel in Figure 12 shows the aggregate effect, independent of type, of knowing type with certainty. This aggregate effect of having complete information depends on the proportion of high-scorers within the demographic groups considered as shown in the bottom panel of Figure 12.Figure 12 suggests that independent of type, levels of mismatch are actually higher for high-SES White youth. We can also see that for Black youth there is little change in bachelor's attainment, and for the rest there are increases in bachelor's attainment. Since high-SES White attainment increases the most, complete knowledge of type might actually increase inequality, despite the gains in attainment for Hispanic and low-SES youth.

The difference of beliefs with respect to $P_{\text{true},i}$ and the actual type will affect the results of the policy analysis. This will be explored in section 5.3. This is a separate question from the role that beliefs play in explaining gaps in the baseline scenario relative to high-SES White youth. What matters for this question is the differences of subjective beliefs and financial assistance between demographic groups. This will be answered in section 5.2 for high-scorers.

5.2 Decomposition

The first question I use the estimated model to answer is, for high-scorers, how much of the gap in bachelor's attainment rates between high-SES White youth versus Black, Hispanic, or low-SES youth, is explained by beliefs? A related question is how much is explained by differences in access to financial resources?

To answer this question, I sequentially set beliefs of all high scorers to the mean value of high-SES White high scorers, then I set the financial assistance of all high scorers to the mean value of high-SES White high scorers. Since these are all high-scorers, human capital is assumed to be equal in the model. Therefore any remaining gaps are due to differences in non-pecuniary utility, entering the model through the distribution of the type I extreme value shocks.

Figure 13 shows mean subjective beliefs about being a high-scorer, and financial assistance by demographic group. Figure 13 shows that high-SES White youth not only receive higher levels of financial assistance on average but are also more optimistic on average. Gaps in average beliefs and financial assistance are also smaller between Black and high-SES White youth.

Figure 14 and Table 8 show the results of the decomposition exercise. In Figure 14, the y-axis shows high-SES White high-scorer bachelor's attainment rate minus the bachelor's attainment rate of the comparison group from the x-axis under the three scenarios in the legend. The rows titled difference in Table 8 provide the numerical values and standard errors for the information shown in the graph. The row titled "% Explained" shows the percentage decline in the gap after each step of the decomposition exercise for each of the demographic groups.

In Figure 14 and Table 8 we see that at each step of the decomposition exercise gaps are narrowed for each of the three comparison groups. However we would not be able to rule out a statistically zero effect of beliefs for Black high scorers, as shown by the large standard errors in Table 8. For Hispanic and low-SES youth however this is not the case. We can reject a null hypothesis that the effect is zero. For these groups beliefs are estimated to explain an estimated 49% of the gap for Hispanic high-scorers, and 38% for low-SES high-scorers.

For all three comparison groups differences in financial assistance are also statistically significant. If the % Explained values in column 2 and 3 are added we can see the portion explained by differences in non-pecuniary utility. For Black and low-SES high-scorers, differences in non pecuniary utility explain nearly 17% of the gap in bachelor's attainment. For Hispanics the estimated portion explained by differences in non-pecuniary utility is only 6%.

The results in this exercise suggests that if Black, Hispanic, or low-SES high scorers are provided with information about their type as well financial assistance then gaps can be narrowed amongst high-scorers. The effect that an intervention like this has on overall inequality regardless of scorer type and how this compares to universal policies will be explored in the next section.

5.3 Policy Analysis: Effects on Inequality and Mismatch

In this section I compare the effects of three policies on mismatch and inequality. Inequality is measured by the difference between the reference group, high-SES White youth, and the three comparison groups; Black, Hispanic, and low-SES youth. In this section gaps are measured independent of type. Mismatch takes the form of under investment in college for high-scorers and over investment for low-scorers. Where high and low scorers are simulated by the model. Realizations of being a high or low scorer depend on human capital measures, grades, and future earnings.

The first of the policies under consideration is a targeted policy that provides free college [28] and information about type to low-SES predicted high-scorers. Notice, for the predicted high scorers, we use only information that would be available to school administrators or policy makers before college, like standardized test scores. In this case, ASVAB measures and adverse behavior indicators are used to predict high scorers for the targeted policy.

The last two policies target everyone regardless of SES and predicted scorer type. These two policies are free college for all and the institution of a tracking policy which provides information about type to all. In the policy analysis free college is implemented through increasing financial assistance from government and institutions to cover tuition sticker prices. Family financial assistance is kept constant. Information is provided by revealing estimated $P_{true,i}$ from the data. This estimate of $P_{true,i}$ only incorporates information that would be available before college completion, ASVAB scores and behavior indicators.

Figure 15 and the rows titled "Difference" in Table 9 shows the difference in bachelor's attainment rates between high-SES White youth and each of the three comparison groups under each scenario. The row "% Change in Gap Relative to Baseline" shows by what percentage the gap changes after implementation of the policy compared to the Baseline. Negative percentage values indicate that the bachelor's attainment gap shrunk, while positive percentage values indicate that the gap increased.

We see that among universal policies free college for all decreases inequality for the three comparison groups,where decreases range between 14.7% to 16.9%. Tracking or better information for everyone actually leads to more inequality where the gap increases at a range of 41.5% to 70%. This is because tracking increases bachelor's attainment for high-SES White youth. Additionally for Black, Hispanic, and low-SES youth, gains in bachelor's attainment from high scorers are offset by decreases in bachelor's attainment rates for low scorers.

[28] Takes the form of increasing government and college assistance to cover sticker price of tuition. Family assistance is kept constant.

The targeted policy providing information and funding to low-SES high scorers decreases inequality the most, decreasing gaps between 25.2% for Black youth, 28.3% for Hispanic youth, and up to 41.8% for low-SES youth. The effect of the policy on Black youth and Hispanic youth is less effective than it is on low-SES youth in general. This is because Black and Hispanic youth benefit from the policy only to the extent that they are also low-SES high-scorers. The policy may be strengthened if information and funding is targeted to Black and Hispanic high scorers regardless of SES.

In Figure 15 gaps still exists after all three policies are implemented. This highlights the important role that disparities in early childhood human capital investment likely still plays in generating inequality. Specifically, even if the targeted policy lead to 100% bachelor's attainment for low-SES high scorers, the fact that discrepancies in early childhood human capital generate a lower proportion of high scorers among low-SES youth, would mean that there would still be inequality in overall attainment.

Finally Table 10 shows the amount of mismatch present in higher education and how it is distributed among high-scorers and low-scorers. We see that 27 % of youth would change their college decisions if they knew their type for certain. The second column shows that this is primarily amongst high-scorers who would likely increase their schooling if they knew their type.

When we enact free college for all this increases to 30.5%, with no decrease in under investment of high-scorers, but a larger 3.3% increase in over investment of low-scorers. As expected the tracking system decreases mismatch the most by almost completely removing all mismatch for low-scorers. This is because it brings all youth closer to the truth by revealing $P_{true,i}$.

The targeted policy decreases overall mismatch but primarily only through high-scorers. The percentage of the population that are mismatched and high-scorers decreases by 8 percentage points under the tracking policy.

Together Table 9-10 shows that if we are interested in policy that decreases inequality with minimal effects on mismatch, then the targeted policy is to be preferred. This is because it not only decreases inequality the most but also decreases mismatch. Tracking increases inequality which would make it undesirable if decreasing inequality was our main policy objective. Free college for all decreases inequality less effectively than the targeted policy and generates more mismatch as well. An additional benefit to the targeted policy is that in practice providing subsidies to only a subset of students is likely much less resource intensive than subsidizing college for all youth. Many of these youth might actually already be qualified for free college, so costs may be even smaller than the model would suggest (Hoxby and Avery 2012, and Dynarski, Libassi, Michelmore, and Owen 2017).

Even if the targeted policy is to be preferred, there are still gaps in bachelor's attainment. This means disparities will likely still exist as long as there are differences in early childhood human capital development as well.

6 Conclusion

In this paper we investigated the role that beliefs played in generating inequality in higher education outcomes for high-scoring youth. In the NLSY97 we found that holding access to resources, demographics, and measures of human capital constant that being more optimistic regarding degree attainment is associated with higher college enrollment, continuation, and completion. We also found that controlling for human capital measures, individual beliefs about enrollment and degree attainment are highly correlated with race, ethnicity, parental education, wealth, and percentage of peers with college plans.

In the quantitative analysis I showed that for high-scorers beliefs contribute between 38-49% of the bachelor's attainment gap for Hispanic and low-SES youth, relative to high-SES White high-scorers. Beliefs explain 33% of the gap for Black high-scorers. However, a zero belief effect for Black high-scorers can not be ruled out. I find that in terms of decreasing inequality while minimizing mismatch, targeted policies that provide information about ability type and funding to low-SES high-scorers are to be preferred to free college for all and instituting a tracking system in the US. This is because the targeted policy not only more effectively closes gaps, but also decreases mismatch. The other two policies exhibit equity efficiency trade offs, where free college for all decreases inequality and increases mismatch, while tracking increases inequality and decreases mismatch.

Therefore this paper shows that information frictions lead to less high scoring youth from all backgrounds under investing in education. These information frictions also contribute to inequality in higher education for Hispanic and low-SES youth. Because of that representation in higher education can be increased through more recruiting of academic high achievers from disadvantaged backgrounds. However because of differences in early childhood human capital development and perhaps college experience, gaps are likely to still persist. Therefore In order to fully close all gaps we must still study the effects of improving K-12 education and household environment.

7 Tables and Figures

7.1 Empirical Analysis: Tables and Figures

Table 1: College Outcomes

VARIABLES	(1) Ever Enrolled	(2) Bachelors Attained	(3) Complete College
Parent Edu	0.0292***	0.0375***	0.0427***
	(0.0048)	(0.0056)	(0.0070)
HH Net Worth ($1000s)	0.0001***	0.0002***	0.0001*
	(0.0000)	(0.0001)	(0.0001)
ASVAB AFQT	0.0055***	0.0057***	0.0035***
	(0.0004)	(0.0004)	(0.0006)
Prob Degree	0.3226***	0.2151***	0.2164***
	(0.0346)	(0.0283)	(0.0491)
Female	0.0806***	0.0847***	0.0411*
	(0.01755)	(0.0186)	(0.0237)
Hispanic	0.0812***	0.0535*	0.0525
	(0.0302)	(0.0286)	(0.0381)
Black	0.1700***	0.1487***	0.1732***
	(0.0266)	(0.0256)	(0.0350)
College GPA			0.1803***
			(0.0152)
Total Govt/Inst Aid ($1000s)			0.0058**
			(0.0027)
Total Fam Aid ($1000s)			0.0075**
			(0.0035)
Total Stud Loan ($1000s)			-0.0081**
			(0.0036)
Geography Controls	Yes	Yes	Yes
Birth Year	Yes	Yes	Yes
Non Cognitive Controls	Yes	Yes	Yes
Peer Effects	Yes	Yes	Yes
Observations	2,133	2,133	1,467
R-squared	0.3499	0.3612	0.3240

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1: Shows the results of three linear probability models. Column (1) and (2) use the whole sample to regress Ever Enrolled and Bachelor's Attained on covariates in the table. Column (3) conditions on those we've observed ever enrolling in college to regress college completion on covariates. Of interest is that the subjective belief variable Prob Degr remains significant and positive after controlling for measures of human capital, access to funding, and parental background

Table 2: Measured Beliefs

VARIABLES	(1) Pct Chance Deg by 30	(2) Prob Enroll
Parent Edu	0.0267***	0.0282***
	(0.0046)	(0.0058)
HH Net Worth ($1000s)	0.0001***	0.0001**
	(0.0000)	(0.0000)
ASVAB AFQT	0.0022***	0.0022***
	(0.0004)	(0.0004)
Peers Coll Plan About 25%	0.0812	0.1289*
	(0.0709)	(0.0766)
Peers Coll Plan About 50%	0.1110*	0.1314*
	(0.0671)	(0.0692)
Peers Coll Plan About 75%	0.1662**	0.1562**
	(0.0670)	(0.0695)
Peers Coll Plan more than 90%	0.2117***	0.1954***
	(0.0675)	(0.0691)
Female	0.0767***	0.0117
	(0.0168)	(0.0205)
Hispanic	0.0435	0.1174***
	(0.0268)	(0.0323)
Black	0.0978***	0.1071***
	(0.0246)	(0.0312)
Geography Controls	Yes	Yes
Birth Year	Yes	Yes
Non Cognitive Controls	Yes	Yes
Observations	1,143	1,139
R-squared	0.2614	0.2304

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Shows results from an OLS specification regressing two measures of beliefs on covariates. Of importance is that subjective beliefs reported before age 18 are highly associated with parental education, race and ethnicity, holding net worth and human capital constant.

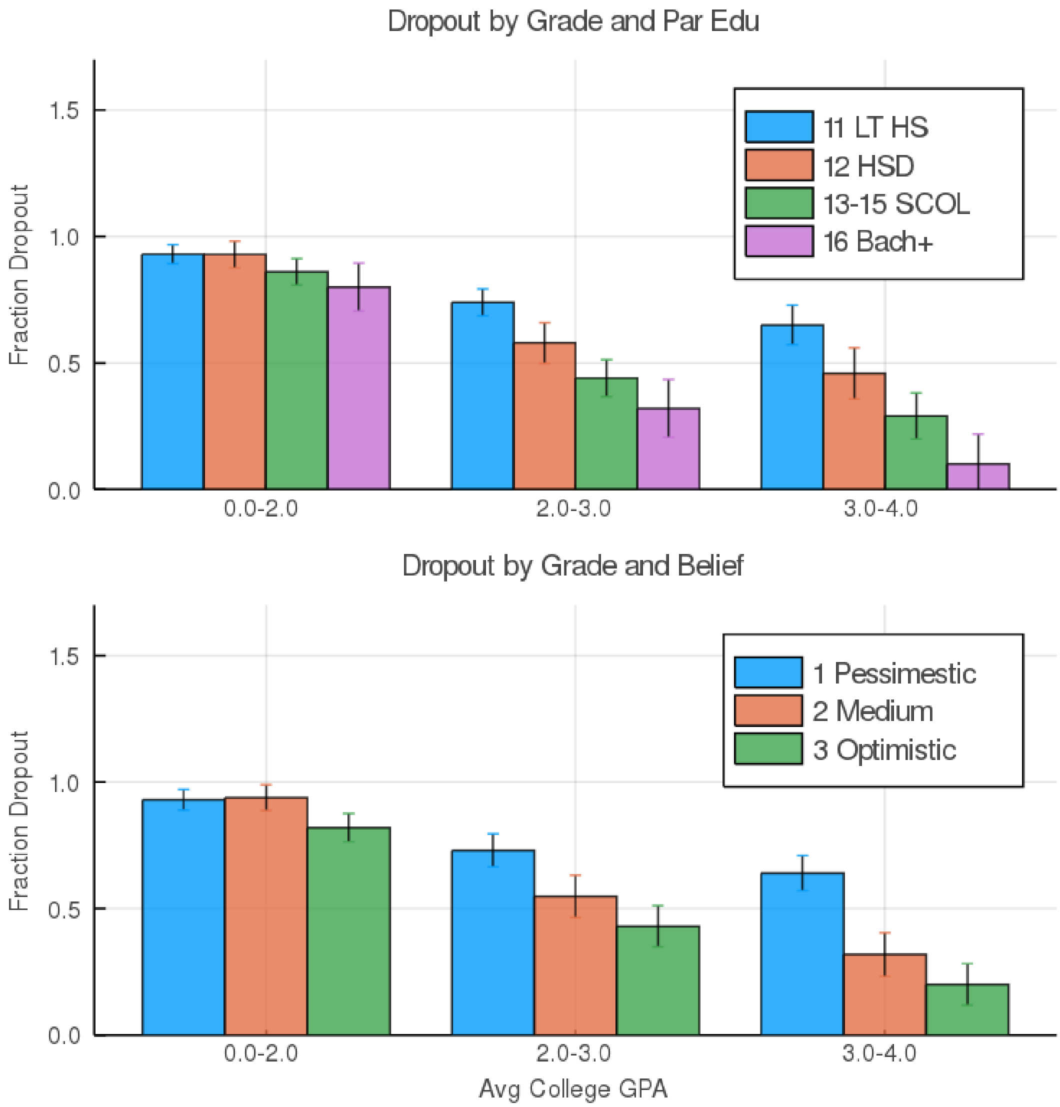

Figure 1: College non-continuation rates conditioned on grades/demographics.

Table 3: Non Continuation Interacted with GPA

VARIABLES	Non Interacted	Interaction GPA 2.0-3.0	Interaction GPA > 3.0
Hispanic	-0.1210**	0.1389	-0.0003
	(0.0500)	(0.0897)	(0.0892)
Black	-0.0588	-0.0100	0.0495
	(0.0396)	(0.0671)	(0.0786)
Parent Edu	-0.0003	-0.0077	-0.0317*
	(0.0096)	(0.0161)	(0.0163)
Prob Deg	0.0677	-0.2748***	-0.2007*
	(0.0544)	(0.1032)	(0.1122)
HH Net Worth ($1000s)	-0.0000		
	(0.0001)		
Total Govt/Inst Aid ($1000s)	-0.0174***		
	(0.0043)		
Total Fam Aid ($1000s)	-0.0112		
	(0.0073)		
Total Stud Loan ($1000s)	-0.0065		
	(0.0051)		
ASVAB AFQT	-0.0009		
	(0.0007)		
GPA 2.0-3.0	-0.1130		
	(0.1185)		
GPA > 3.0	-0.2031*		
	(0.1170)		
Geography Controls	Yes		
Birth Year	Yes		
Non Cognitive Controls	Yes		
Observations	1,028		
R-squared	0.2576		

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Displays the results of an OLS regression of college non continuation on covariates, where GPA categories are interacted with the self reported belief variable Prob Degr, as well as Parent Edu. The second and third column show the results of the interacted coefficients, while the first column displays the stand alone coefficients.

7.2 Model Predictions

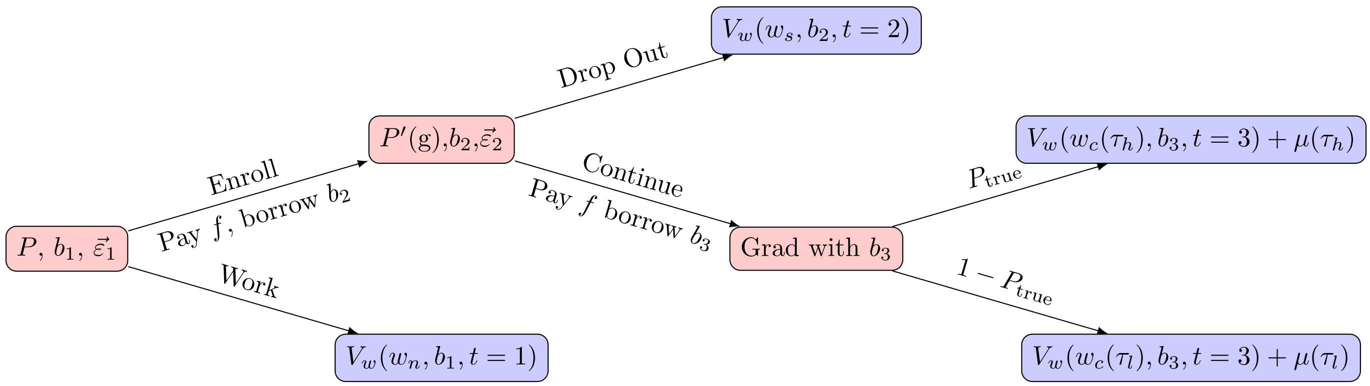

Figure 2: Decision tree representation of the quantitative model. Red nodes represent key stages of the model where decisions are made or different outcomes are realized.

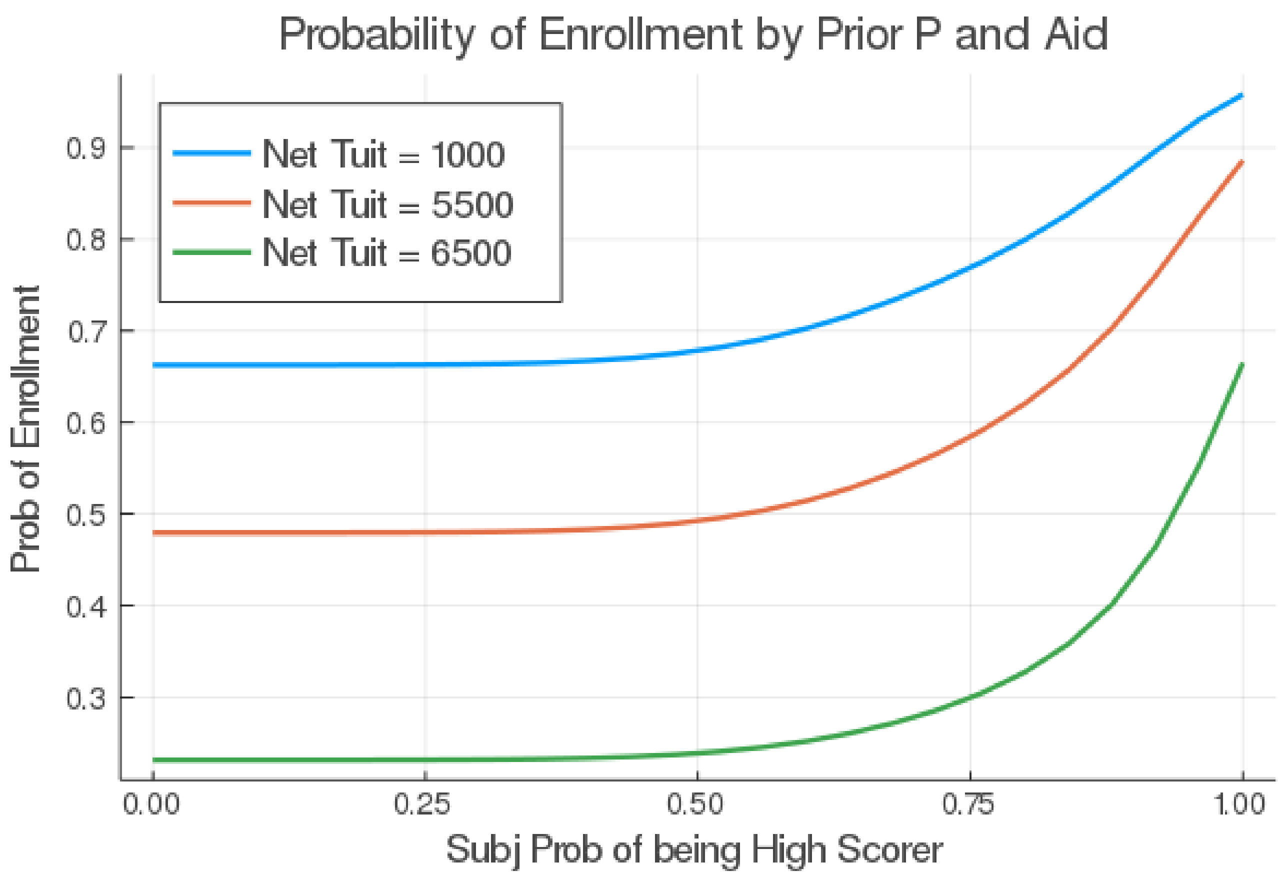

Figure 3: Model predicted probability of college enrollment by net tuition and prior subjective belief of being a high-scorer. Net tuition is the "sticker price" of tuition minus any financial aid received from family, government or colleges.

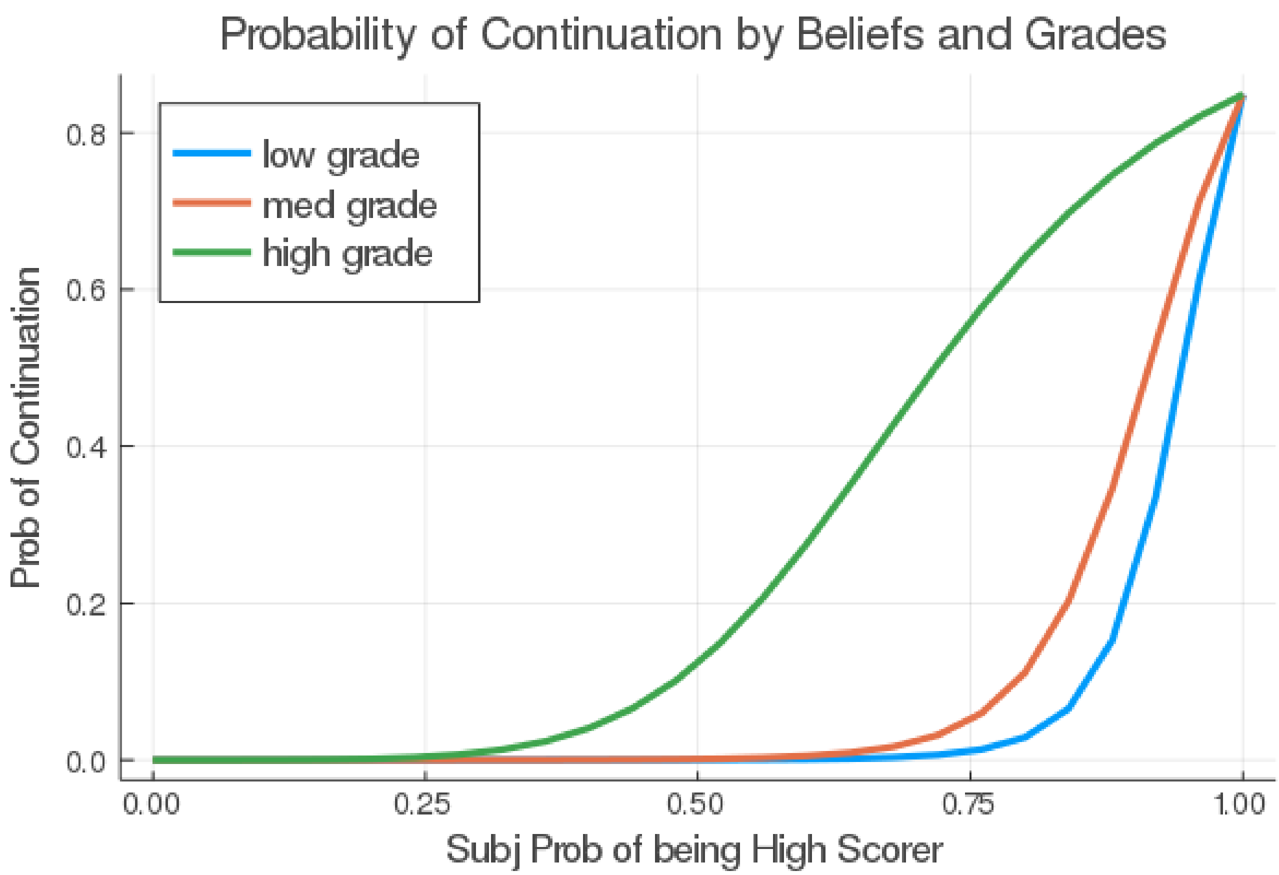

Figure 4: Model predicted probability of college continuation by average GPA realized before the second stage after the first stage.

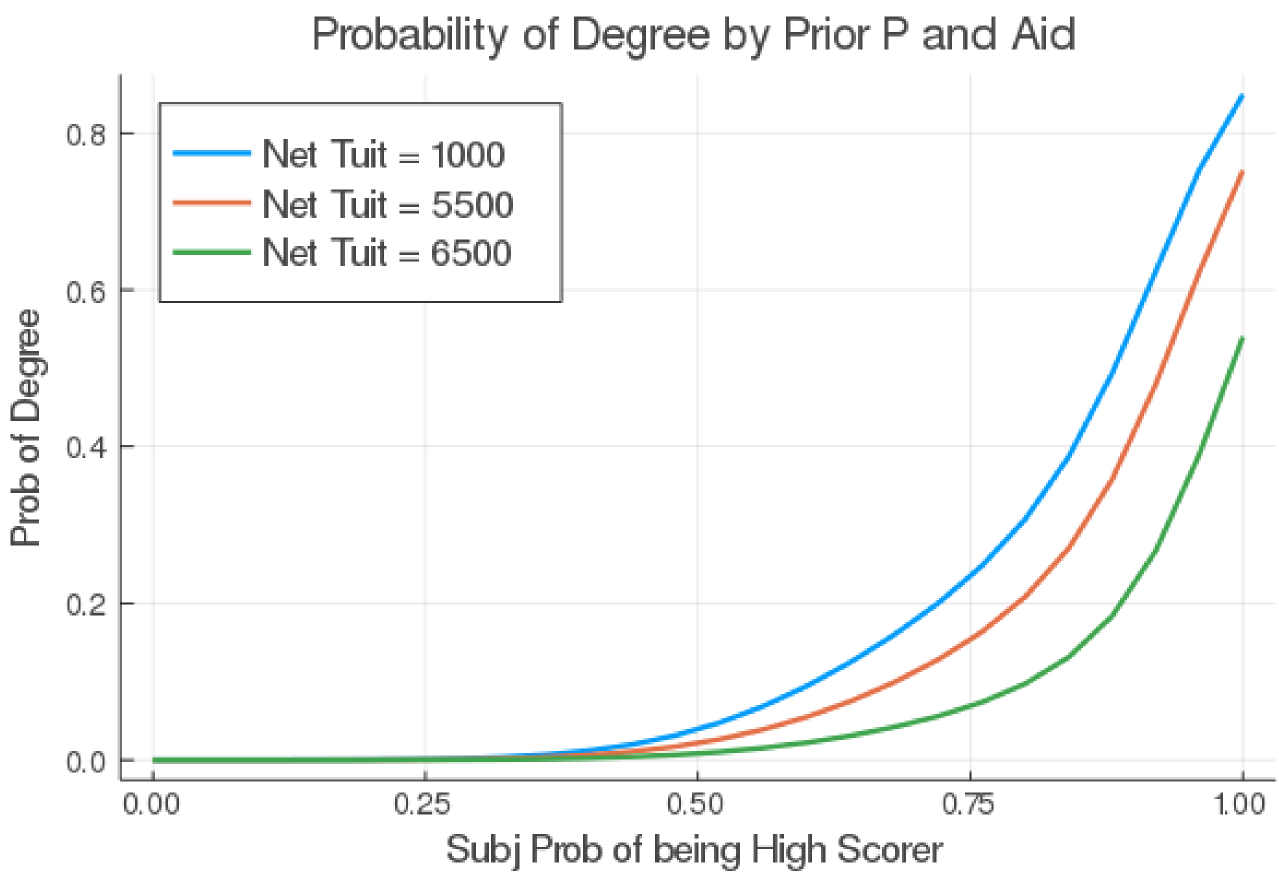

Figure 5: Model predicted probability of bachelor's attainment, which is enrollment and continuation, by net tuition and prior subjective belief of being a high-scorer. Net tuition is the "sticker price" of tuition minus any financial aid received from family, government or colleges.

7.3 Quantitative Figures and Tables

Table 4: Preset Parameters prior to Estimation

Parameter	Set Value	Description
β	0.94	Discount rate
γ	2.0	Coeff. of Rel Risk Aversion
$(1+r)$	β^{-1}	Int rate
T	24	Number of periods representing two years
$B_{c,1}$	\$16,600	College Borrowing limits pd 1
$B_{c,2}$	\$35,600	College Borrowing limits pd2

Table 4: Discount rate, coefficient of relative risk aversion, interest rate are set to values similar to other papers. T is intended to capture lifespan from 18-66 or working life since each period lasts two years. College borrowing limits are set to average student loan levels in the first two years and last two years of college.

Table 5: Key Internal Parameter Results

Parameter	Parameter Description	Target	Target Description
$\gamma_{p,0}$	Belief Constant	$\beta_{C,0}, \beta_{C,G_m}, \beta_{C,G_h}$	Constant, Coefficient med, high GPA on continuation
$\mu_c(\tau)$	Type dependent non pecuniary utility	$\beta_{C,0}, \beta_{C,G_m}, \beta_{C,G_h}$	Constant, Coefficient med, high GPA on continuation
$\gamma_{p,b}$	Belief: Meas Belief	$\beta_{E,B}$	Coefficient Meas Belief on enrollment
$\gamma_{p,h}$	Belief: P-Edu HSD	$\beta_{C,PH}$	Coefficient $Pedu_{hsg}$ on continuation
$\gamma_{p,s}$	Belief: P-Edu SCOL	$\beta_{C,PS}$	Coefficient $Pedu_{scol}$ on continuation
$\gamma_{p,c}$	Belief: P-Edu Bach	$\beta_{C,PB}$	Coefficient $Pedu_{bach}$ on continuation
$\mu_{d,0}$	Non Pecun Util: Black 1st Gen Col Stud	$\beta_{E,0} + \beta_{E,1G}$	Constant and $FirstGen$ Coefficient on enrollment
$\mu_{d,C}$	Non Pecun Util: Col Edu Parents	$\beta_{E,0}$	Constant Coefficient on enrollment
$\mu_{d,W}$	Non Pecun Util: White	$\beta_{E,W}, \beta_{C,W}$	$White$ Coefficient on enrollment,continuation
$\mu_{d,H}$	Non Pecun Util: Hispanic	$\beta_{E,H}, \beta_{C,H}$	$Hisp$ Coefficient on enrollment,continuation
$tuit_1$	Tuition Pd 1	$\beta_{E,F_2}, \beta_{E,F_3}$	$T2(Finaid), T3(Finaid)$ Coefficient on enrollment
$tuit_2$	Tuiton Pd 2	$\beta_{C,F_2}, \beta_{C,F_3}$	$T2(Finaid), T3(Finaid)$ Coefficient on continuation

Table 5: Description of Internally Estimated Parameters and moment targets identifying parameters. See equations (16) and (17) to see full regression specification.

Table 6: External Estimation Results: Average Earnings

Parameter	Estimated Annual Value	Description
w_n	$\$29,584$	Non College Earnings
w_s	$\$45,026$	Some College Earnings
$w_s(\tau_l)$	$\$51,277$	Low type college earnings
$w_s(\tau_h)$	$\$65,841$	High type college earnings

Table 6: Expected value of earnings from finite mixture model by education choice and type.

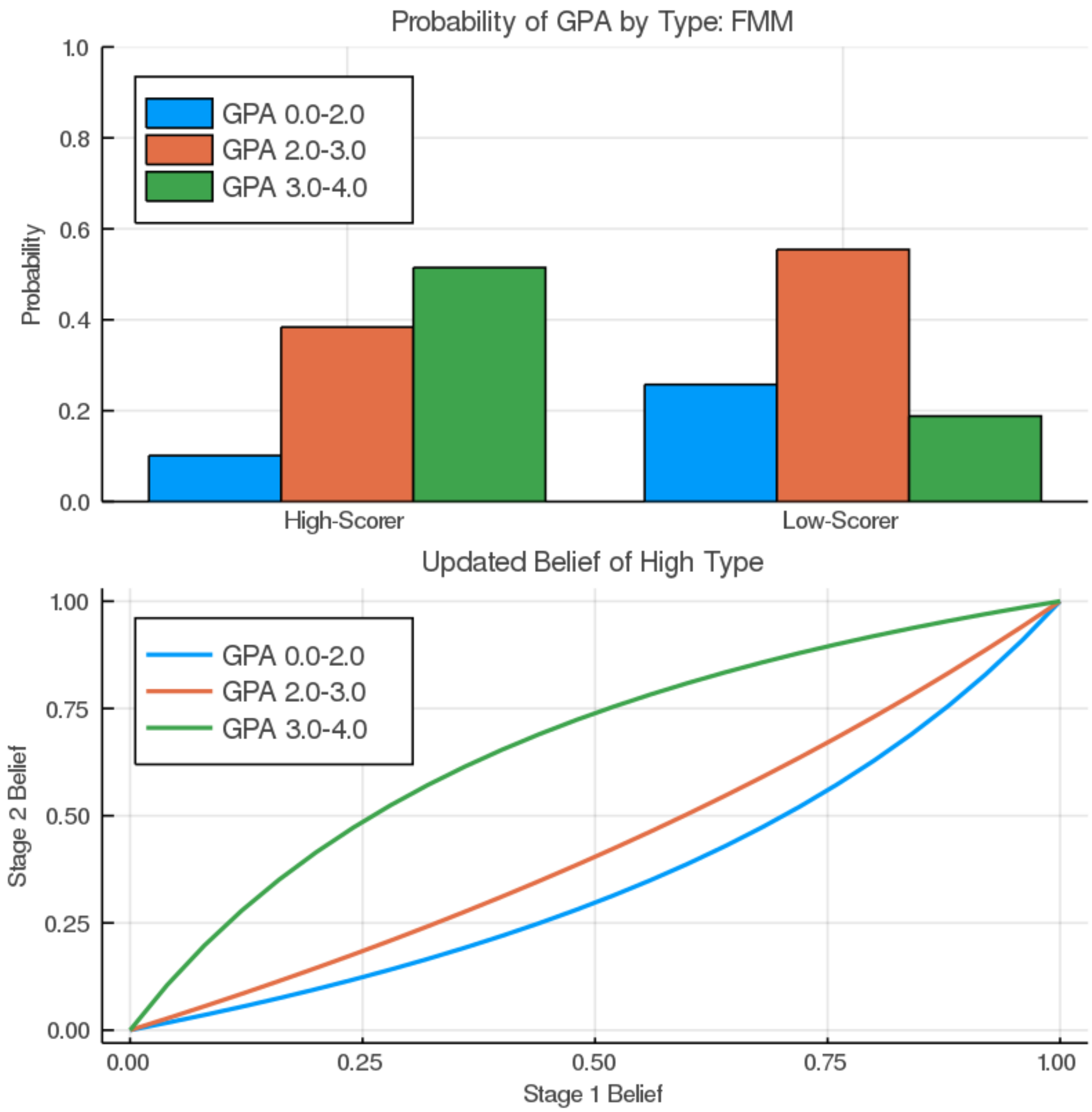

Figure 6: The top panel shows grade probability condition on being a high-scorer or low-scorer. While the bottom panel shows how prior subjective beliefs on the x-axis are updated to the posterior belief on the y-axis after grade realization.

Table 7: Key Internal Parameter Results

Parameter	Description	Estimate
$\gamma_{p,0}$	Belief Constant	0.0057
		(0.0133)
$\gamma_{p,b}$	Belief: Meas Belief	0.88***
		(0.0103)
$\gamma_{p,h}$	Belief: P-Edu HSD	0.026**
		(0.0116)
$\gamma_{p,s}$	Belief: P-Edu SCOL	0.028***
		(0.0103)
$\gamma_{p,c}$	Belief: P-Edu Bach	0.055***
		(0.0102)
$\mu_{d,0}$	Non Pecun Util: Black 1st Gen Col Stud	-0.000056
		(0.000044)
$\mu_{d,C}$	Non Pecun Util: Col Edu Parents	0.00004
		(0.000037)
$\mu_{d,W}$	Non Pecun Util: White	0.000017
		(0.000028)
$\mu_{d,H}$	Non Pecun Util: Hispanic	0.000023
		(0.000034)
$\mu_c(\tau_h)$	Non Pecun Util high	0.00052***
		(0.000065)
$\mu_c(\tau_l)$	Non Pecun Util high	-0.0028***
		(0.00031)
$tuit_1$	Tuition Pd 1	$7583.61***
		(120.5)
$tuit_2$	Tuiton Pd 2	$6972.45***
		(16.05)

Boot strapped standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Description of key internally estimated parameter results from indirect inference estimation. Standard errors are bootstrapped standard errors.

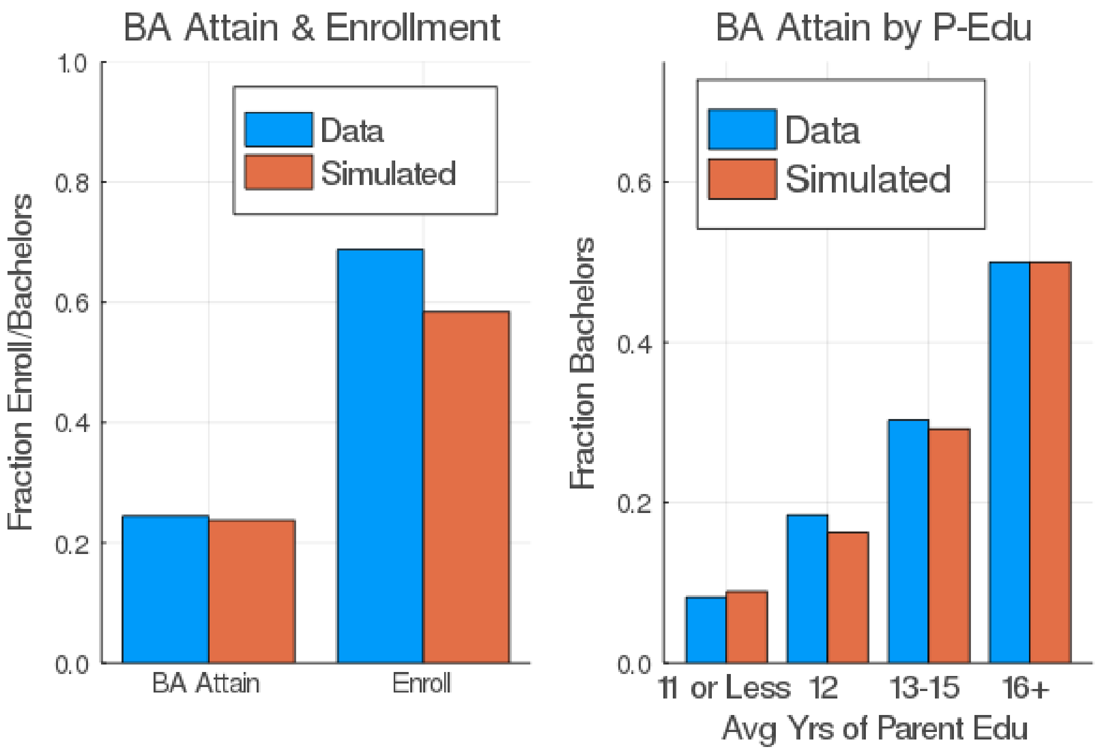

Figure 7: Fit of the Estimated Model: Enrollment, bachelors (BA) attainment. The blue bars are from the NLSY97 and the orange bars are simulated from the estimated model.

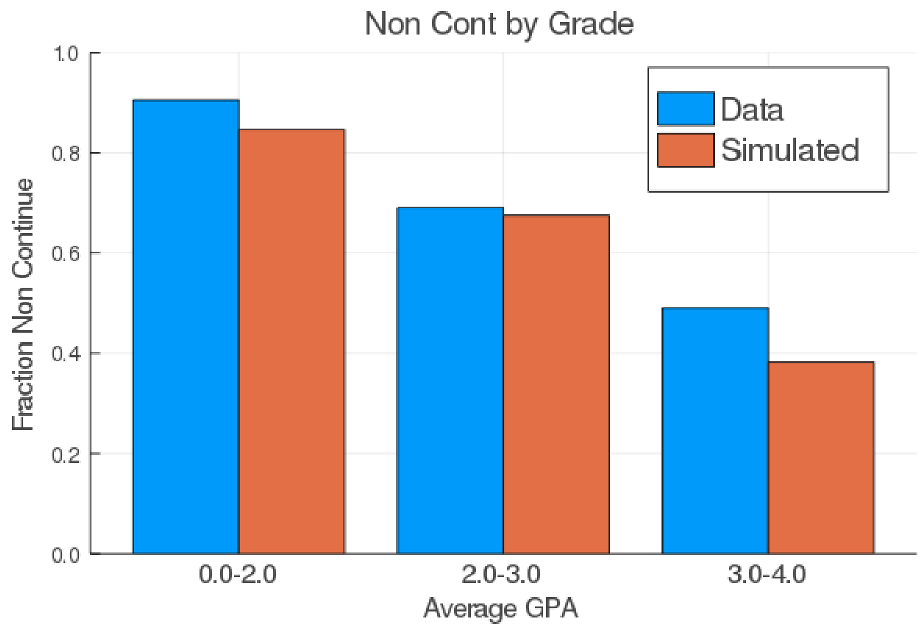

Figure 8: Fit of the Estimated Model: non-continuation by GPA level. The blue bars are from the NLSY97 and the orange bars are simulated from the estimated model.

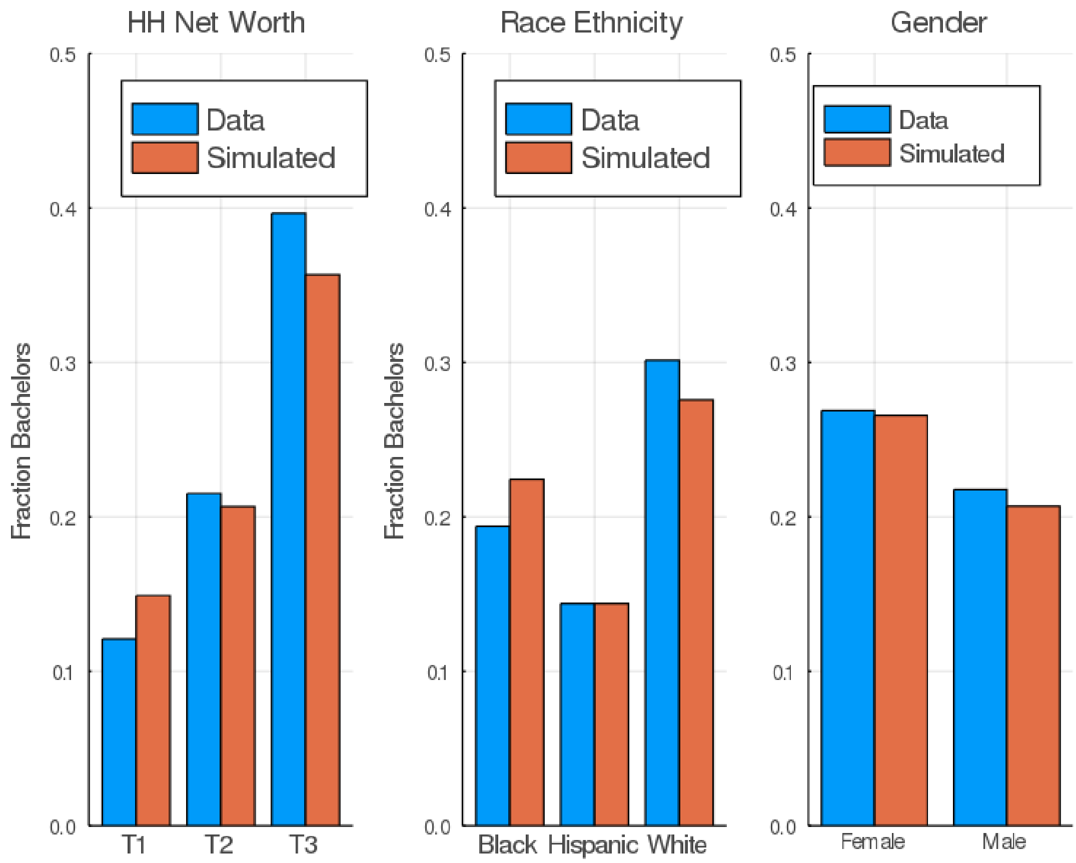

Figure 9: Fit of the Estimated Model: Bachelor's attainment by demographics.The blue bars are from the NLSY97 and the orange bars are simulated from the estimated model.

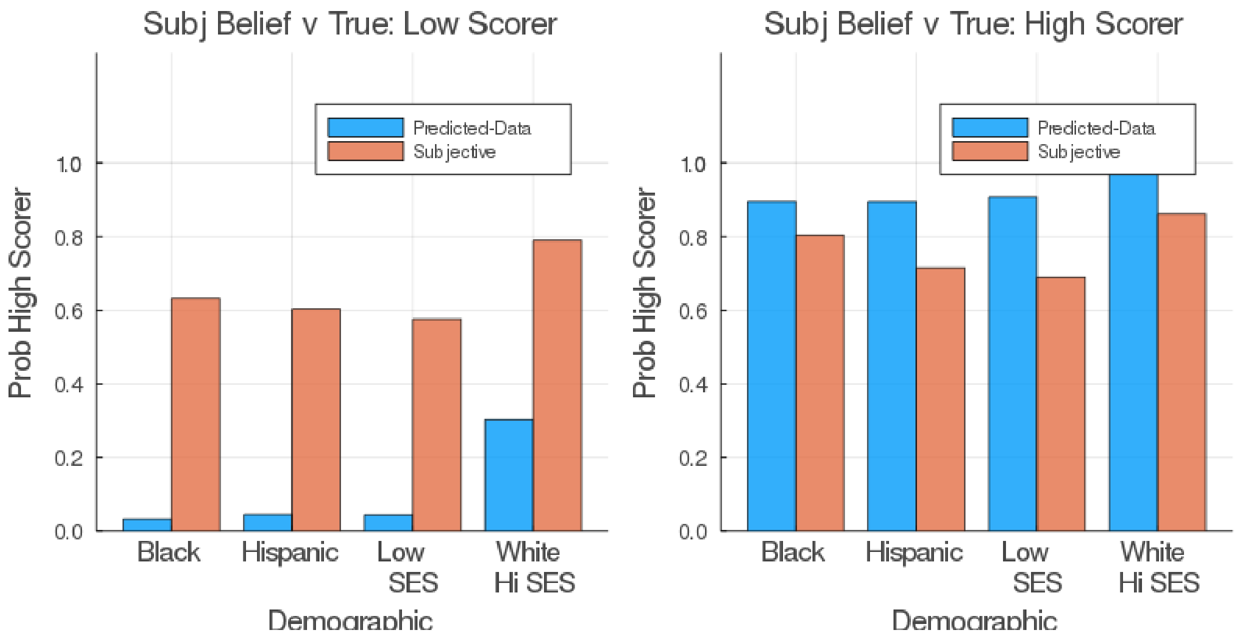

Figure 10: Compares the mean FMM estimate of prob high-scorer vs the mean subjective belief of being a high-scorer by scorer type. The left hand side is only predicted low-scorers, and the right hand side is only high-scorers.

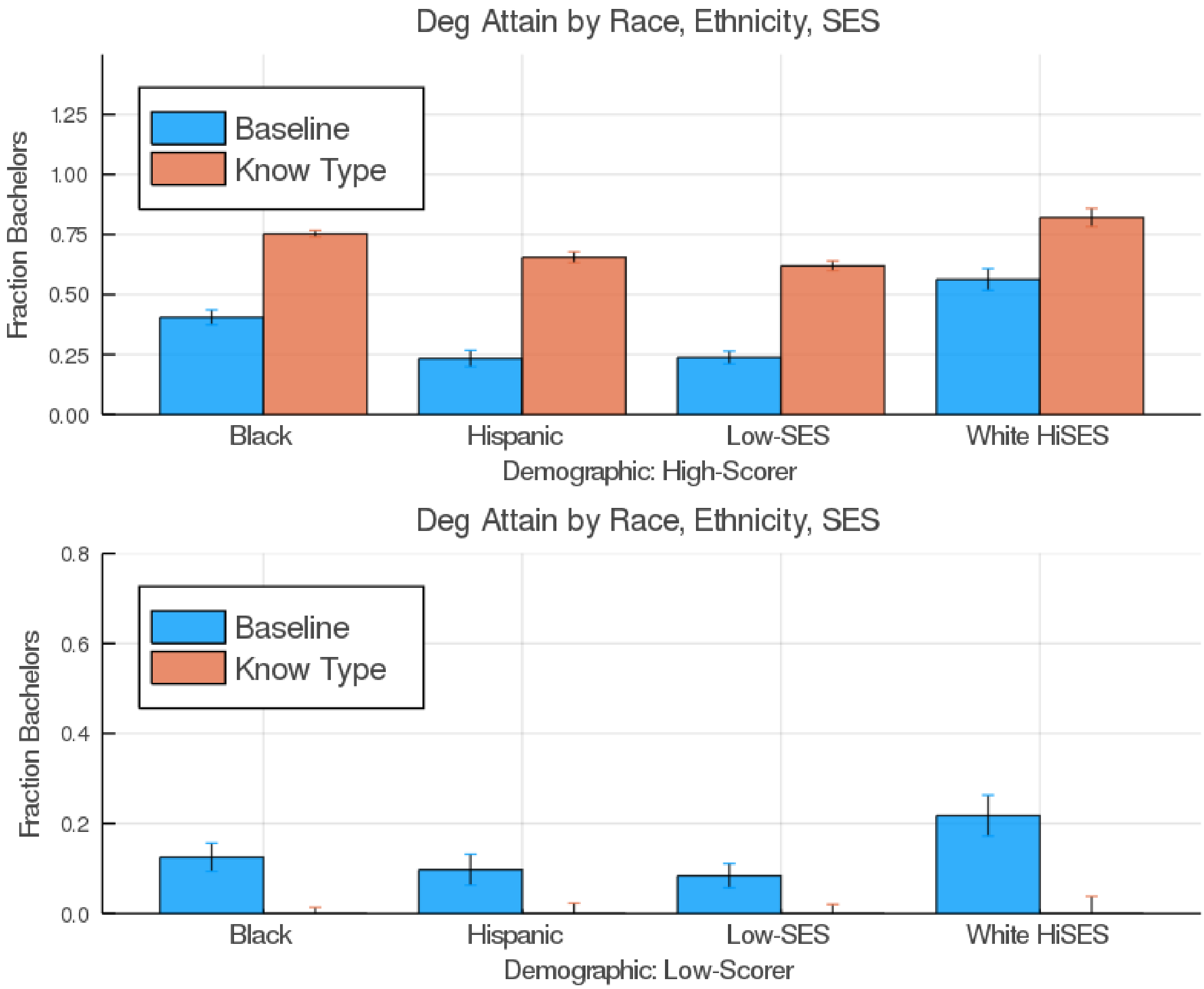

Figure 11: Shows difference in bachelor's attainment under baseline model and under scenario where youth know their true type with certainty. This graph looks at high-scorers by demographic group in the top panel, and low-scorers by group in the bottom panel.

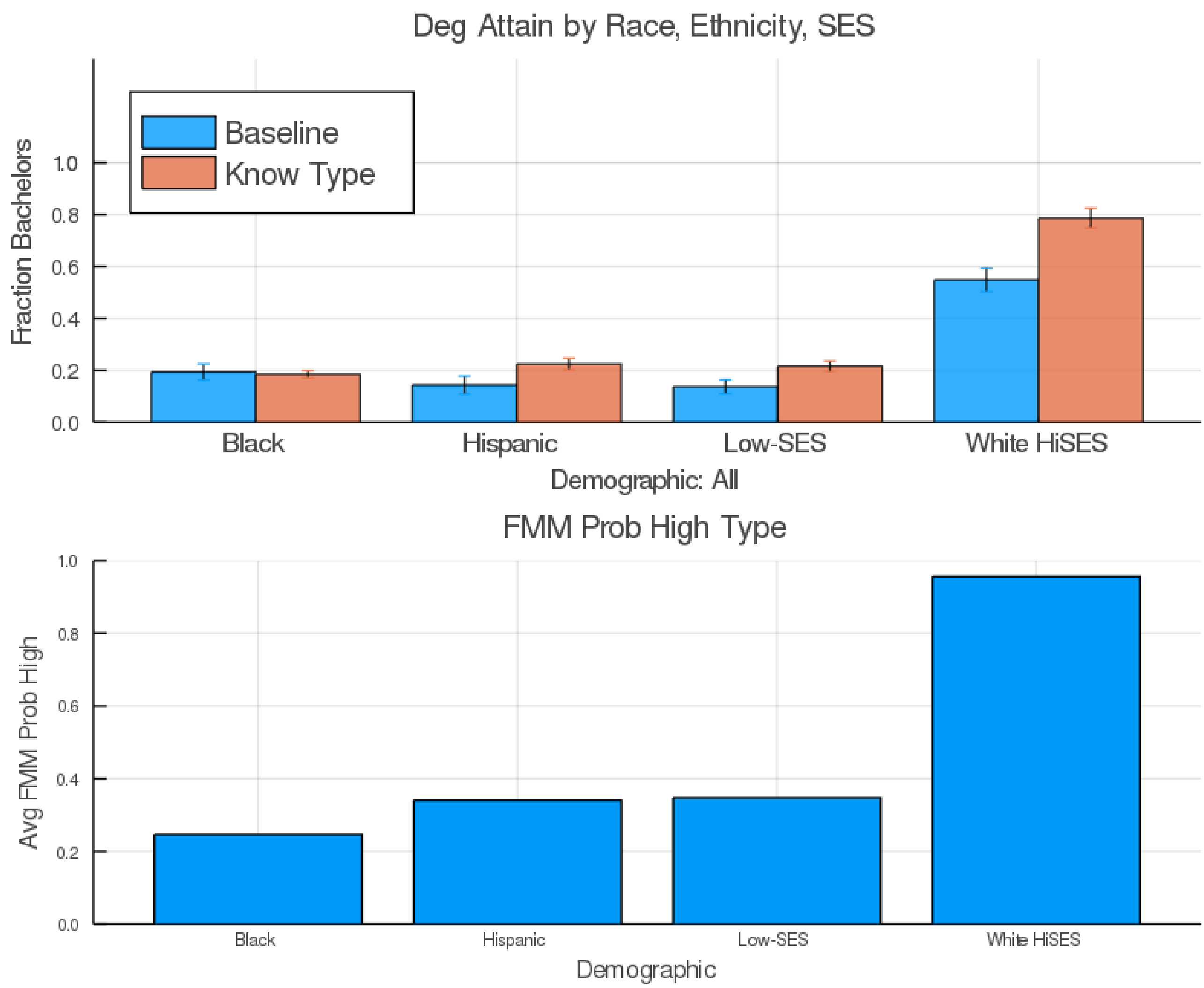

Figure 12: Top panel shows difference in bachelor's attainment regardless of type under baseline model and under scenario where youth know their true type with certainty. The bottom panel shows the proportion of high-scorers by demographic group in order to explain aggregate results.

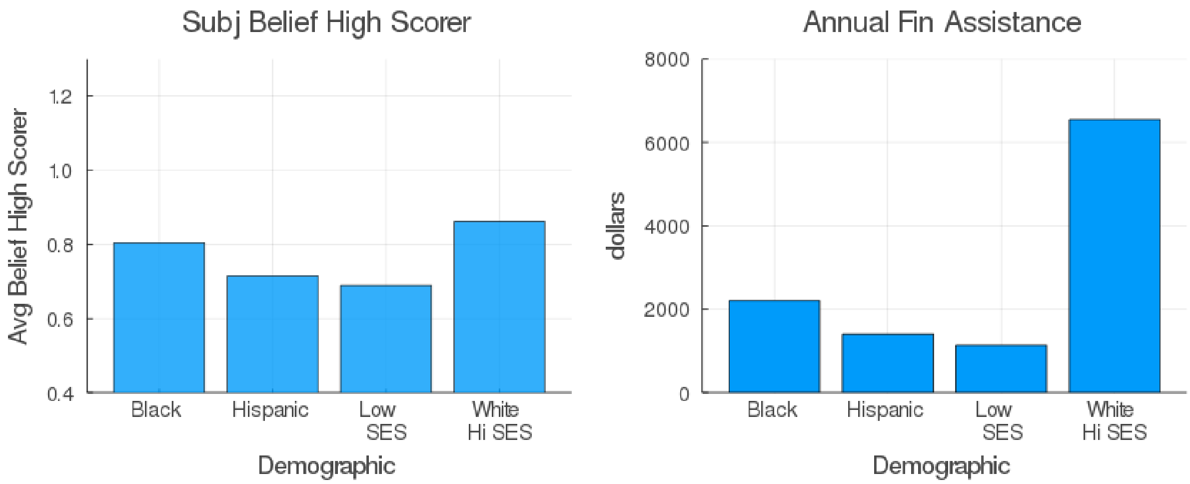

Figure 13: Shows the estimated variables relating to causal mechanism by demographic group. The left panel is the average subjective belief of being a high-scorer which is a function of measured beliefs in the NLSY97 and parental education. The right panel is predicted total financial assistance by demographics which is the sum of family assistance and govt/college aid.

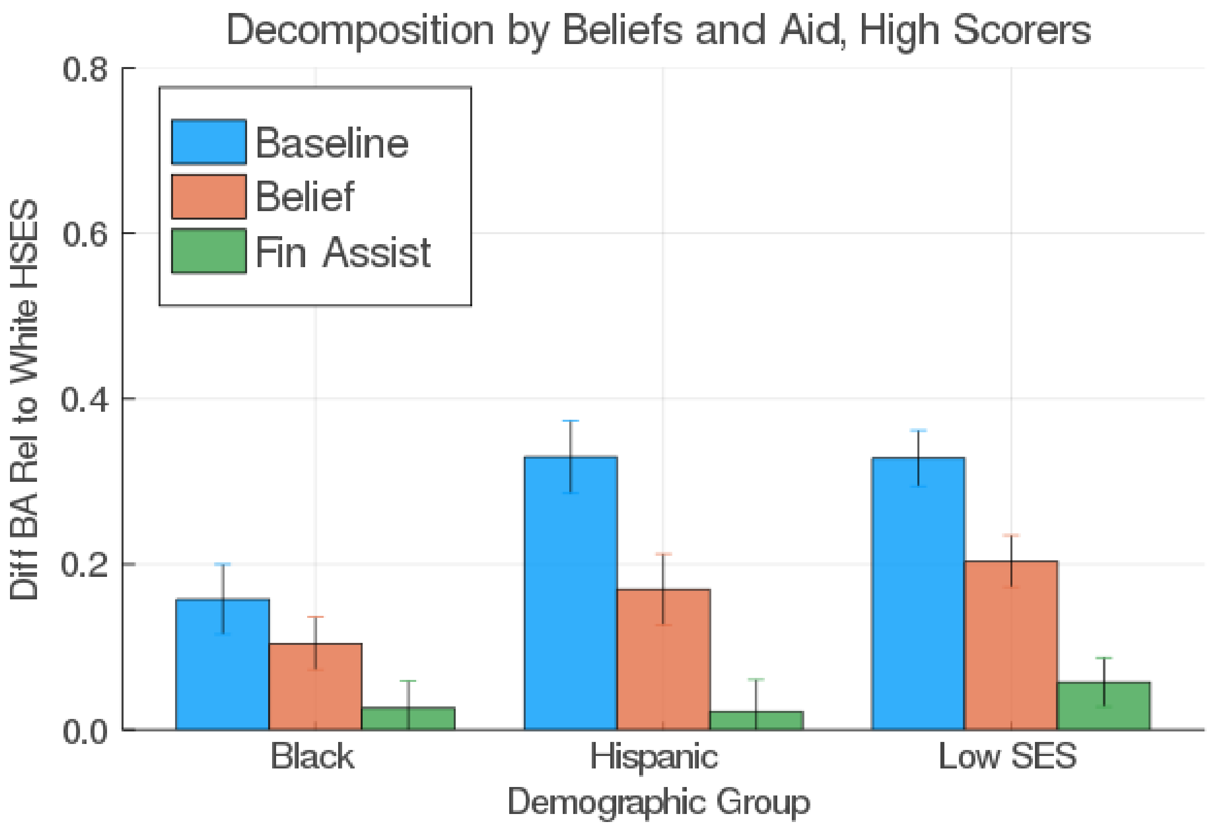

Figure 14: Difference in bachelors attainment relative to high-SES White high-scorers after sequentially equalizing variables. Standard errors are bootstrapped standard errors.

Table 8: Mechanism Decomposition: High Scorers

Demographic	(1) Baseline	(2) Beliefs Equal	(3) Fin Assist Equal
Black			
Difference	15.8***	10.4	2.6**
	(4.24)	(3.19)	(3.32)
% Explained		33 %	50%***
		(20.4)	(11.22)
Hispanic			
Difference	33***	16.9***	2.2***
	(4.39)	(4.29)	(3.85)
% Explained		49 %***	45%***
		(13.67)	(6.34)
Low SES			
Difference	32.8***	20.5***	5.7***
	(3.39)	(3.13)	(2.96)
% Explained		38%***	45%***
		(10.97)	(6.17)
White High SES Bachelor's attain	56		

Boot strapped standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Shows how much of gaps in bachelor's attainment are explained by beliefs and financial assistance for high-scorers. The row "Difference" is the high-SES White bachelor's attainment rate minus the bachelor's attainment rate for the comparison group. The "% Explained" rows show how much of the difference in the baseline scenario is explained by each mechanism. For "Baseline" values on "Difference" rows and all values in "% Explained row", null hypothesis tested is whether the value is equal to zero. For the Beliefs Equal and Fin Assist Equal values on Difference rows, null hypothesis tested is whether the decrease relative to previous step in decomposition is equal to zero.

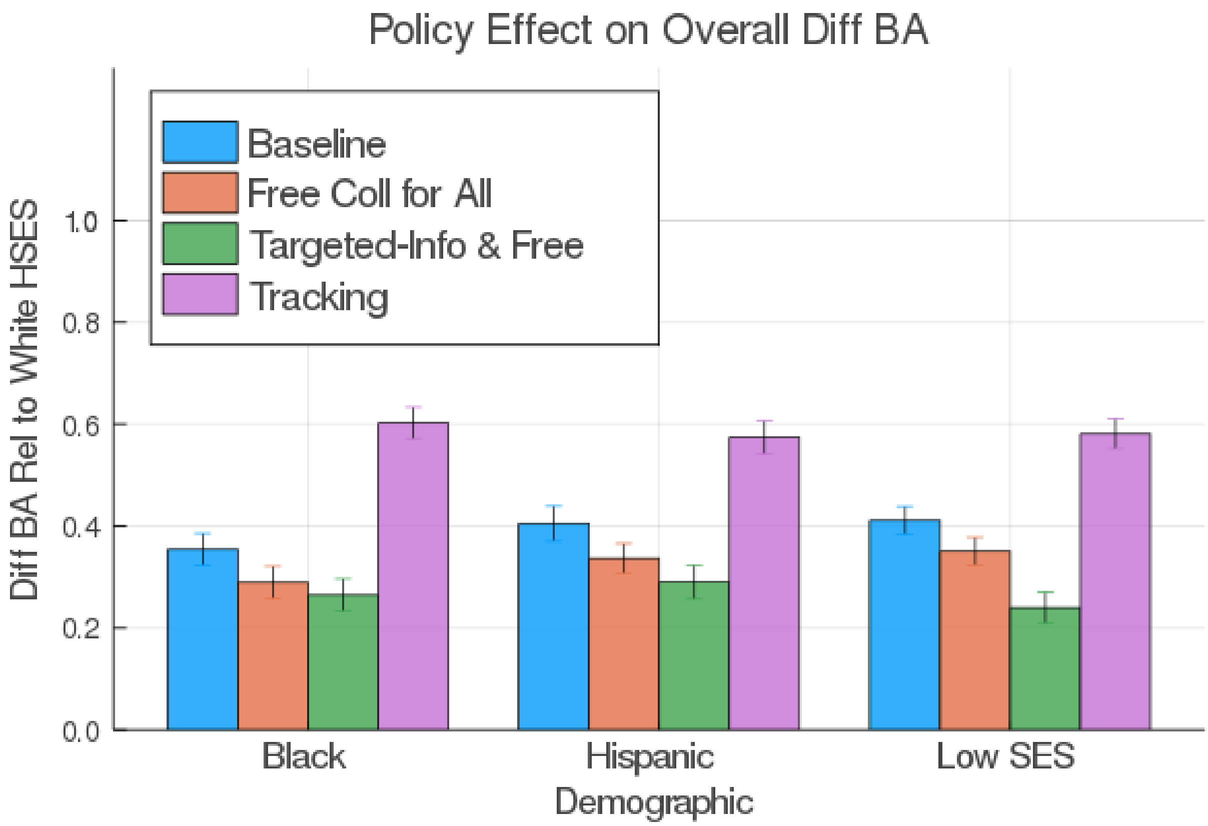

Figure 15: Shows differences in type independent bachelors attainment relative to high-SES White high-scorers after policy implementation. Standard errors are bootstrapped standard errors.

Table 9: Policy Effect on Overall Inequality

Demographic	Baseline	Free College For All for All	Tracking: Info to All to All	Recruiting: Targeted Info & Free
Black				
Difference	35.4***	28.95**	60.22***	26.5***
	(3.11)	(3.16)	(3.10)	(3.18)
% Change in Gap Relative to Baseline		-18.3** %	70%***	-25.2 % ***
		(8.59)	(8.43)	(8.65)
Hispanic				
Difference	40.5***	33.6**	57.42***	29.02***
	(3.45)	(2.94)	(3.23)	(3.33)
% Change in Gap Relative to Baseline		-16.9 %**	42%***	-28.26%***
		(7.04)	(7.74)	(7.96)
Low SES				
Difference	41.1***	35.05**	58.2***	23.9***
	(2.69)	(2.71)	(2.95)	(3.08)
% Change in Gap Relative to Baseline		-14.7%**	41.5%***	-41.8%***
		(6.38)	(6.95)	(7.27)
White High SES Bachelor's attain	54.8			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Shows the effect of the three policies on the difference in bachelor's attainment rates for Black, Hispanic, and low-SES youth relative to high-SES White youth, independent of scorer type. The row "Difference" is just the high-SES White bachelor's attainment rate minus the bachelor's attainment rate for the comparison group in the panel. "% Change in Gap Relative to Baseline" is calculated as the percentage change in bachelor's attainment differences after the policy. For "Baseline" column on "Difference" rows and values in "% Change in Gap" rows, null hypothesis tested is whether each individual value is equal to zero. For the corresponding policy values in "Difference" rows, hypothesis tested is whether the change in the gap relative to the corresponding gap in the Baseline column is equal to zero.

Table 10: Mismatch: Percentage of Population Switch with Type Knowledge

Policy	% Pop Mismatched Overall	% Pop Mismatched High-Scorer	% Pop Mismatched Low-Scorer
Baseline	27.1 %	21.3 %	5.8 %
Free College For All	30.5%	21.5 %	9.1 %
Tracking: Info for All	4.4 %	4.1 %	0.3 %
Targeted: Recruiting	19.1%	13.3 %	5.9%

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Shows the percentage of the population in the simulations that would change their decision to obtain a bachelor's degree or not if they knew their type. Values in the second and third columns or each row sum to the first column since they are percentage of population that are mismatched and high-scorer and percentage of population that are mismatched and low-scorers.

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A Appendix

A.1 More Empirical Facts

Table 11: Summary Statistics by Race Ethnicity

VARIABLES	(1) All	(2) White	(3) Hispanic	(4) Black
Enrolled in College	0.717	0.740	0.626	0.670
Bachelors or More	0.301	0.336	0.171	0.222
Parent Edu Lt 12	0.220	0.158	0.541	0.288
Parent Edu 12	0.216	0.202	0.176	0.313
Parent Edu 13-15	0.388	0.434	0.200	0.302
Parent Edu 16+	0.176	0.205	0.083	0.098
Avg Parent Edu	13.02	13.43	11.15	12.37
HH Net Worth ($1000s)	185.8	226.4	80.68	56.04
Pct Peers ColPlan	66.5	68.7	60.8	68.5
Prob Enroll	0.751	0.758	0.734	0.732
Prob Degree	0.777	0.793	0.679	0.767
College GPA	2.65	2.79	2.41	2.14
Total Govt/Inst Aid ($1000s)	2.3	1.96	1.65	2.71
Total Fam Aid ($1000s)	1.64	1.92	0.96	0.60
ASVAB AFQT	54.73	61.20	40.32	32.15
Ever Stole	0.0671	0.0608	0.0943	0.0779
Ever Violence	0.161	0.141	0.165	0.265
Ever Sex before 15	0.182	0.145	0.186	0.375
Sample Size	2133	1188	404	541

Table 12: Summary Statistics by Parent Education

VARIABLES	(1) All	(2) Lt 12	(3) 12	(4) 13-15	(5) 16 +
Enrolled in College	0.717	0.447	0.614	0.814	0.944
Bachelors or More	0.301	0.0787	0.208	0.359	0.544
Hispanic	0.116	0.285	0.092	0.062	0.056
Black	0.146	0.191	0.212	0.114	0.082
Avg Parent Edu	13.02	10.10	12.00	13.77	16.00
HH Net Worth ($1000s)	185.8	53.53	123.8	201.7	375.8
Pct Peers ColPlan	66.5	58.2	62.3	69.7	75.2
Prob Enroll	0.751	0.572	0.713	0.812	0.882
Prob Degree	0.777	0.633	0.691	0.840	0.917
College GPA	2.65	2.21	2.62	2.68	2.98
Total Govt/Inst Aid ($1000s)	2.3	2.40	1.68	1.93	2.29
Total Fam Aid ($1000s)	1.64	0.42	0.85	1.64	3.01
ASVAB AFQT	54.73	32.47	49.53	60.13	75.08
Ever Stole	0.0671	0.0928	0.0492	0.0750	0.0422
Ever Violence	0.161	0.233	0.176	0.147	0.0903
Ever_Sex before 15	0.182	0.295	0.210	0.152	0.0845
Sample Size	2133	586	493	736	318

Table 13: Financial Assistance

VARIABLES	(1) Any Family Aid	(2) Total Fam Aid	(3) Any Govt/Coll Aid	(4) Total Govt/Coll Aid
Parent Edu	0.0346***	0.1854***	-0.0006	-0.0793
	(0.0072)	(0.0607)	(0.0078)	(0.0751)
HH Net Worth	0.0003***	0.0050***	-0.0002***	0.0001
	(0.0001)	(0.0009)	(0.0001)	(0.0007)
ASVAB AFQT	0.0030***	0.0114**	0.0022***	0.0216***
	(0.0006)	(0.0045)	(0.0006)	(0.0067)
Female	0.0322	-0.0604	0.0574**	0.2054
	(0.0249)	(0.2464)	(0.0276)	(0.3452)
Hispanic	0.0198	0.5455*	0.0995**	-0.5875
	(0.0403)	(0.3057)	(0.0441)	(0.5116)
Black	-0.0134	0.0212	0.1932***	0.9796**
	(0.0393)	(0.2425)	(0.0386)	(0.4450)
Geography Controls	Yes	Yes	Yes	Yes
Birth Year	Yes	Yes	Yes	Yes
Non Cognitive Controls	Yes	Yes	Yes	Yes
Robust Standard Errors	Yes	Yes	Yes	Yes
Peer Effects	Yes	Yes	Yes	Yes
Observations	1,467	929	1,467	940
R-squared	0.1478	0.2416	0.0503	0.0379

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Shows the results from OLS specifications regressing financial assistance variable on covariates. Columns (1) and (2) are for family assistance while in college, while (3) and (4) are for government or college financial aid while in college, including grants, scholarships, and work study. Columns (1) and (3) are linear probability models since they are indicators for if any assistance was provided.

Table 14: Oaxaca-Blinder Decomp: Subj Prob Degree: White vs Hispanic/Black

VARIABLES	White Hisp overall	White Hisp explained	White Hisp unexplained	White Black overall	White Black explained	White Black unexplained
Parent Edu		0.0604***	0.0822**		0.0317***	0.0582
		(0.0105)	(0.0326)		(0.0056)	(0.0473)
HH Net Worth (1000$s)		0.0139***	0.0092		0.0158***	-0.0032
		(0.0043)	(0.0084)		(0.0050)	(0.0079)
ASVAB AFQT		0.0537***	-0.0218		0.0682***	-0.0317
		(0.0083)	(0.0306)		(0.0094)	(0.0276)
Female		-0.0002	-0.0161		-0.0033**	0.0070
		(0.0014)	(0.0176)		(0.0016)	(0.0202)
% Peers College Plan		0.0128***	-0.0505		0.0127***	-0.0168
		(0.0036)	(0.0600)		(0.0035)	(0.0581)
Ever Stole more $50		0.0002	0.0007		0.0000	-0.0060
		(0.0005)	(0.0053)		(0.0002)	(0.0044)
Ever Violence		0.0014	-0.0090		0.0038*	-0.0106
		(0.0013)	(0.0086)		(0.0021)	(0.0088)
Ever Sex bf15		0.0051**	-0.0194*		0.0191***	-0.0113
		(0.0024)	(0.0103)		(0.0051)	(0.0123)
Ref Mean (White)	0.7659***			0.7659***		
	(0.0093)			(0.0093)		
Comp Mean	0.7053***			0.7375***		
	(0.0162)			(0.0154)		
difference	0.0606***			0.0285		
	(0.0187)			(0.0180)		
explained	0.1470***			0.1477***		
	(0.0124)			(0.0115)		
unexplained	-0.0864***			-0.1192***		
	(0.0208)			(0.0194)		
Constant			34.6180			5.9500
			(23.3366)			(21.4124)
Observations	1,592	1,592	1,592	1,716	1,716	1,716
N Comparison	404	404	404	528	528	528
N Reference (White)	1188	1188	1188	1188	1188	1188

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Shows Oaxaca Blinder decomposition results explaining unconditional differences in mean self reported probability of degree for Hispanic/Black youth compared to White youth. Explained is portion explained by differences in explanatory variables and unexplained column is portion explained by coefficient results in race/ethnicity separate regressions.

Table 15: Oaxaca-Blinder Decomp: Enroll: White vs Hispanic/Black

VARIABLES	White Hisp overall	White Hisp explained	White Hisp unexplained	White Black overall	White Black explained	White Black unexplained
Parent Edu		0.0674***	0.0634		0.0333***	0.0559
		(0.0139)	(0.0448)		(0.0069)	(0.0588)
HH Net Worth ($1000s)		0.0152***	-0.0030		0.0163**	0.0021
		(0.0055)	(0.0133)		(0.0063)	(0.0134)
ASVAB AFQT		0.1317***	-0.0324		0.1740***	-0.1048***
		(0.0132)	(0.0427)		(0.0142)	(0.0354)
Belief Var		0.0198***	-0.0254		0.0081	0.0591
		(0.0065)	(0.0627)		(0.0052)	(0.0532)
Female		-0.0003	0.0191		-0.0085***	-0.0506**
		(0.0017)	(0.0244)		(0.0030)	(0.0242)
% Peers College Plan		0.0052	0.0246		-0.0005	0.1512**
		(0.0035)	(0.0820)		(0.0035)	(0.0699)
Ever Stole more $50		0.0002	-0.0033		-0.0000	-0.0052
		(0.0005)	(0.0071)		(0.0001)	(0.0050)
Ever Violence		0.0011	-0.0189		0.0055**	-0.0037
		(0.0012)	(0.0116)		(0.0028)	(0.0111)
Ever Sex bf15		0.0029	-0.0061		0.0106*	-0.0107
		(0.0021)	(0.0132)		(0.0055)	(0.0143)
Ref Mean (White)	0.7239***			0.7239***		
	(0.0130)			(0.0130)		
Comp Mean	0.5743***			0.6534***		
	(0.0246)			(0.0207)		
difference	0.1496***			0.0705***		
	(0.0278)			(0.0244)		
explained	0.2432***			0.2388***		
	(0.0190)			(0.0179)		
unexplained	-0.0936***			-0.1683***		
	(0.0269)			(0.0240)		
Constant			3.9612			19.0688
			(31.3443)			(25.9906)
Observations	1,592	1,592	1,592	1,716	1,716	1,716
N Comparison	404	404	404	528	528	528
N Reference (White)	1188	1188	1188	1188	1188	1188

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Shows Oaxaca Blinder decomposition results explaining unconditional differences in mean college enrollment for Hispanic/Black youth compared to White youth. Explained is portion explained by differences in explanatory variables and unexplained column is portion explained by coefficient results in race/ethnicity separate regressions.

Table 16: Oaxaca-Blinder Decomp: College Cont: White vs Hispanic/Black

VARIABLES	White Hisp overall	White Hisp explained	White Hisp unexplained	White Black overall	White Black explained	White Black unexplained
Parent Edu		0.0905***	0.1009		0.0514***	0.0910
		(0.0178)	(0.0655)		(0.0102)	(0.0828)
HH Net Worth (1000$s)		0.0167*	-0.0197		0.0189*	-0.0249**
		(0.0091)	(0.0255)		(0.0105)	(0.0122)
ASVAB AFQT		0.0675***	0.0653		0.1078***	-0.0541
		(0.0146)	(0.0695)		(0.0175)	(0.0612)
Belief Var		0.0139**	-0.0010		0.0082*	0.0484
		(0.0057)	(0.1128)		(0.0044)	(0.0809)
College Avg GPA		0.0602***	-0.0533		0.1141***	-0.0520
		(0.0118)	(0.0934)		(0.0132)	(0.0865)
Total Govt/Inst Aid		0.0013	0.0155		-0.0052*	0.0065
		(0.0013)	(0.0214)		(0.0029)	(0.0159)
Total Fam Aid		0.0086**	-0.0143		0.0115**	-0.0258**
		(0.0041)	(0.0152)		(0.0051)	(0.0115)
College Stud Loan		-0.0035	-0.0004		-0.0001	-0.0175
		(0.0022)	(0.0126)		(0.0009)	(0.0179)
Female		0.0002	0.0087		-0.0034	0.0261
		(0.0011)	(0.0330)		(0.0031)	(0.0351)
% Peers College Plan		0.0039	0.0725		0.0049	0.0541
		(0.0048)	(0.1214)		(0.0060)	(0.0924)
Ever Stole more $50		0.0003	0.0007		0.0015	0.0086
		(0.0013)	(0.0085)		(0.0016)	(0.0068)
Ever Violence		0.0008	-0.0019		0.0033	0.0064
		(0.0028)	(0.0140)		(0.0037)	(0.0111)
Ever Sex bf15		0.0090**	-0.0453***		0.0246***	-0.0397***
		(0.0045)	(0.0147)		(0.0080)	(0.0150)
Ref Mean (White)	0.5790***			0.5790***		
	(0.0168)			(0.0168)		
Comp Mean	0.3586***			0.4124***		
	(0.0312)			(0.0262)		
difference	0.2204***			0.1666***		
	(0.0354)			(0.0311)		
explained	0.2695***			0.3373***		
	(0.0250)			(0.0239)		
unexplained	-0.0491			-0.1708***		
	(0.0356)			(0.0322)		
Constant			31.0493			-21.1310
			(41.3287)			(34.1851)
Observations	1,104	1,104	1,104	1,221	1,221	1,221
N Comparison	237	237	237	354	354	354
N Reference (White)	867	867	867	867	867	867

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16: Shows Oaxaca Blinder decomposition results explaining unconditional differences in mean college continuation for Hispanic/Black youth compared to White youth. Explained is portion explained by differences in explanatory variables and unexplained column is portion explained by coefficient results in race/ethnicity separate regressions.

Table 17: Average Log Earnings

VARIABLES	(1) HS or Less	(2) Some Coll	(3) Bach Deg or More	(4) Returns SCol	(5) Returns Bach
Parent Edu	0.0133	-0.0010	-0.0271*	-0.0143	-0.0404
	(0.0196)	(0.0155)	(0.0136)	(0.0281)	(0.0268)
HH Net Worth	0.0010***	0.0002	0.0003**	-0.0008**	-0.0007**
	(0.0003)	(0.0002)	(0.0001)	(0.0003)	(0.0003)
Prob Deg	0.2397**	0.2016*	0.1355	-0.0380	-0.1042
	(0.1022)	(0.1058)	(0.1085)	(0.1561)	(0.1703)
ASVAB AFQT	0.0048**	0.0007	0.0059***	-0.0041*	0.0011
	(0.0018)	(0.0011)	(0.0013)	(0.0022)	(0.0024)
Female	-0.7265***	-0.4011***	-0.3544***	0.3254***	0.3722***
	(0.0751)	(0.0656)	(0.0558)	(0.0996)	(0.0935)
Hispanic	-0.0803	0.2513***	0.0649	0.3316***	0.1452
	(0.0954)	(0.0800)	(0.0938)	(0.1244)	(0.1338)
Black	-0.4046***	-0.2088**	0.1860*	0.1959	0.5907***
	(0.0995)	(0.0844)	(0.1019)	(0.1303)	(0.1424)
Constant	9.9542***	10.2503***	10.7313**	0.2961	0.7771*
	(0.2779)	(0.3658)	(0.2925)	(0.4697)	(0.4246)
Observations	666	696	771	2,133	2,133
R-squared	0.2594	0.1254	0.1258	0.2738	0.2738

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17: Shows the OLS results from regressing log average earnings (where 1 is added to values to include zeros) on education seperately (first three columns) then interacted with all variables (Last two columns).

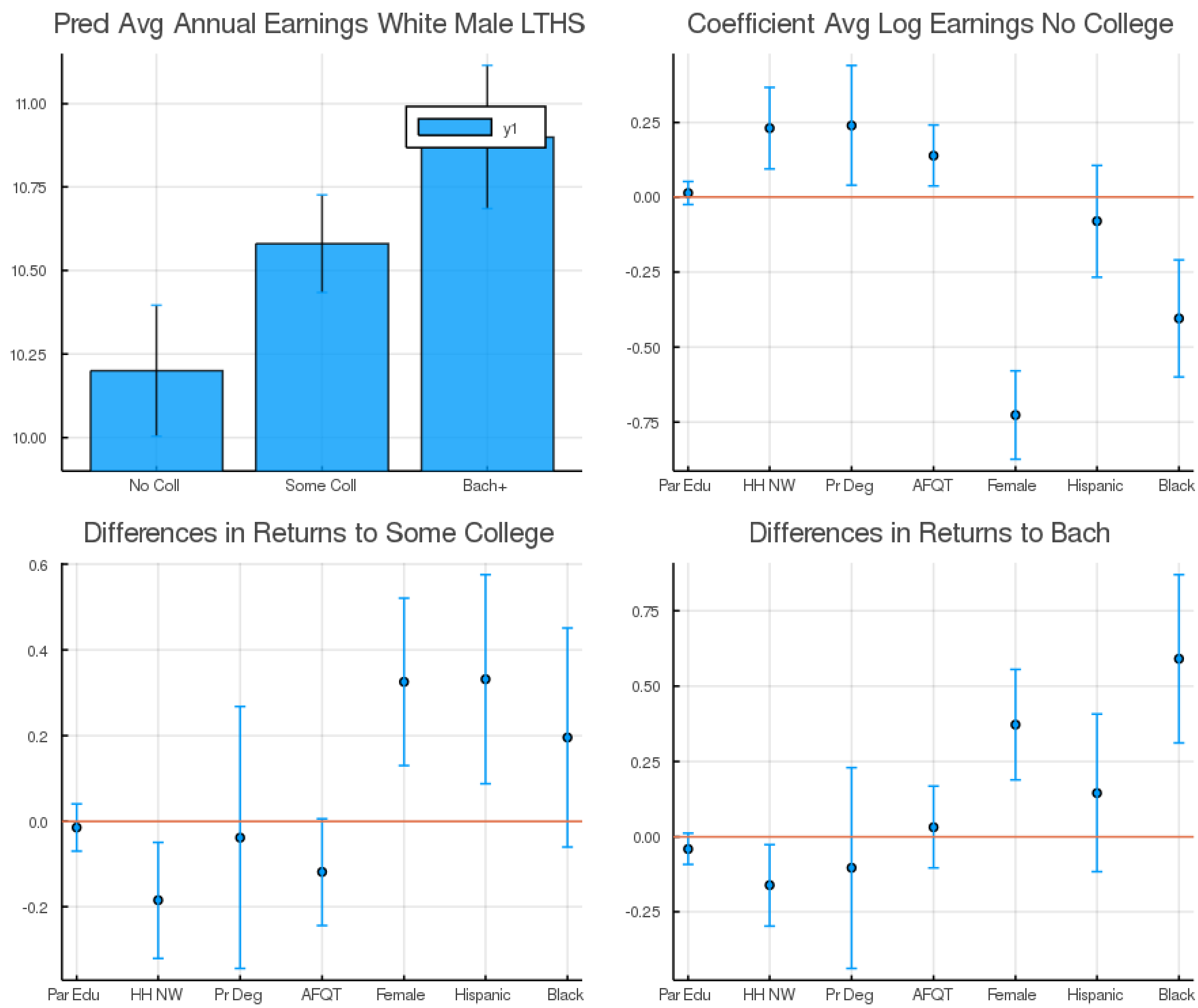

Figure 16: Shows predicted average earnings from Table 17 in top left panel, while other three panels plot coefficients to provide scale for the results.

A.2 Likelihood Function: Finite Mixture Model

In this section, I briefly go over the likelihood function used to estimate the finite mixture model. The finite mixture model, uses the four continuous ASVAB test scores (Arithmetic Reasoning, Mathematical Knowledge, Paragraph Comprehension, and Word Knowledge), the three discrete adverse behavior measures (Sex before age 15, ever committed violence at start of survey, and ever stole greater than \$50 at start of the survey), discrete college GPA categories (0.0-2.0, 2.0-3.0, 3.0-4.0), and earnings as measurement equations.

These measurement equations are functions of the latent type τ for scorer type. The finite mixture model also controls for demographic selection in enrollment and college continuation. The probability that $\tau = \tau_h$ is also allowed to differ by demographic group.

Equation (a.1) shows the full likelihood function. The first line is the product of the likelihood contribution of all four of the cognitive ability measures, the ASVAB test scores, which are observed for the whole sample. In the likelihood function $\phi(\cdot)$ is the pdf for the standard normal distribution, where the first argument is normalized subtracting its mean and dividing the difference by the standard deviation.

The second line of (a.1) is the product of the likelihood contribution of observing the three discrete non cognitive ability measures. $\Phi(\cdot)$ is the CDF of the standard normal distribution where Z^*_{i,j_n} is normalized by subtracting its mean and dividing the difference by the standard deviation.

The third line of (a.1) is the probability that an individual has less than or equal to 12 years of schooling, multiplied by the pdf of observing log earnings $\ln w_{i,s}$, where log earnings are assumed to be normally distributed. The fourth and fifth lines are similar to line three of (a.1) in that we multiply the probability of observing schooling type, by the likelihood of earnings given schooling type. Lines three and four differ in that we also multiply by the likelihood of observing GPA $g = g_k$, since this information is only seen if agents enroll.

Notice type τ_k enters earnings for college graduates, grade probabilities, and cognitive ability measurements. Demographic information X_i enters probability of being high type, as well as probability of enrollment then non completion $\text{Prob}(s \in (12, 16))$ and probability of having a bachelor's degree $\text{Prob}(s \geq 16)$.

$$(a.1) \qquad f(\vec{Z}_i, w_i, g_i; \tau_k, X_i, s) = \Pi_{j_c} \phi(Z^*_{i,j_c}; \tau_k) \times$$
$$\Pi_{j_n} \Phi(Z^*_{i,j_n}; \tau_k)^{1(Z^*_{i,j_n})} \times (1 - \Phi(Z^*_{i,j_n}; \tau_k))^{1-1(Z^*_{i,j_n})}$$
$$\times [\text{Prob}(s \leq 12 | X_i)) \phi(\ln w_{i,s})]^{1(s<12)}$$
$$\times [\text{Prob}(s \in (12, 16) | X_i) \Pi_{g_k} \pi(g_k | \tau_k)^{1(g=g_k)} \phi(\ln w_{i,s})]^{1(s \in (12,16))}$$
$$\times [\text{Prob}(s \geq 16) | X_i) \Pi_{g_k} \pi(g_k | \tau_k)^{1(g=g_k)} \phi(\ln w_{i,s}; \tau_k)]^{1(s \geq 16)}$$

A.3 Finite Mixture Model Results

Table 18: Funding by Demographic: External Estimate

VARIABLES	OLS log Family Aid	OLS log Gov Coll Aid
Intercept	-0.963	3.67***
	(0.637)	(0.722)
Parent Edu	0.347***	0.0455
	(0.045)	(0.0513)
HH Net Worth ($1000s)	0.0032***	-0.0012***
	(0.0004)	(0.00046)
Black	-0.718***	1.093***
	(0.217)	(0.246)
Hispanic	-0.144	0.311
	(0.258)	(0.292)
Female	0.182	0.587
	(0.171)	(0.194)
Birth Yr 1981	0.329	0.0436
	(0.245)	(0.278)
Birth Yr 1983	0.114	-0.0238
	(0.247)	(0.280)
Birth Yr 1984	0.415*	0.161
	(0.245)	(0.277)
Observations	1,467	1,467
R-squared	0.1554	0.0345

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18: Shows the results from the OLS estimates of log financial assistance from family and government/college. A value of one is added to account for zeros. Total financial assistance in the model is calculated by summing the predicted financial assistance from family with the predicted financial assistance from governments or colleges.

Table 19: Prob by Demographic: FMM

VARIABLES	Logit Prob High Type	Logit Prob Enroll	Logit Prob Continue
Intercept	-1.029***	-0.991***	-3.367 ***
	(0.306)	(0.163)	(0.333)
Parent HS	0.930***	0.610***	0.460***
	(0.286)	(0.132)	(0.212)
Parent Some Coll	1.296***	1.407***	0.756***
	(0.341)	(0.151)	(0.204)
Parent Bach	2.635***	2.58***	1.159***
	(0.663)	(0.272)	(0.217)
HH Net Worth Tercile 2	0.358*	0.396***	0.337*
	(0.185)	(0.129)	(0.172)
HH Net Worth Tercile 3	1.044***	1.063***	0.637***
	(0.348)	(0.169)	(0.185)
Hispanic	-0.655***	0.307**	-0.040
	(0.201)	(0.145)	(0.189)
Black	-1.488***	0.441	0.354**
	(0.467)	(0.139)	(0.164)
Female	0.224	0.629***	0.043
	(0.249)	(0.105)	(0.119)
GPA Med			2.167***
			(0.240)
GPA High			1.475***
			(0.239)

Boot Strapped standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: Shows the results from the finite mixture model that estimates the proportion of high types by demographic group in the first column and predicted enrollment and continuation by demographic group in the second and third column.

Table 20: Cognitive and Non Cognitive Measurement: FMM

VARIABLES	Linear ASVAB Math Knowledge	Linear ASVAB Arithmetic Reasoning	Linear ASVAB Word Knowledge	Linear ASVAB Paragraph Comprehension
Intercept	-9.048***	-11.077***	-12.970***	-10.231***
	(1.176)	(1.097)	(1.104)	(1.149)
High Type	14.877***	13.710***	13.968***	14.449***
	(2.295)	(2.126)	(2.155)	(2.228)
Variance	6.988***	7.05***	6.479***	6.077***
	(0.503)	(0.428)	(0.470)	(0517)

	Probit Ever Sex bf 15	Probit Ever Violence	Probit Ever Stole gt 50
Intercept	-0.488***	-0.864***	-1.454***
	(0.204)	(0.142)	(0.115)
High Type	-0.646	-0.209	-0.128
	(0.400)	(0.260)	(0.206)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20: Shows the results from the finite mixture model for human capital variables. High Type is a binary variable if agent is high type.

Table 21: Grades and Earnings: FMM

VARIABLES	Logit Prob GPA (2.0-3.0)	Logit Prob GPA (3.0-4.0)
Intercept	0.767***	-0.315
	(0.110)	(0.225)
High Type	0.565***	1.939***
	(0.177)	(0.352)
	Linear Earnings	
Intercept	9.879***	
	(0.038)	
Ever Enrolled	0.423***	
	(0.043)	
Bachelors	0.124*	
	(0.067)	
Bachelor*High Type	0.256***	
	(0.075)	
Std Error Unobserved Shock	0.83***	
	(0.0223)	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 21: Shows the results from the finite mixture model. High Type is a binary variable if agent is high type, For earnings, expected log non college earnings are given by the intercept. Expected log some college earnings are the intercept added to the Ever Enrolled coefficient. For expected log college earnings add the Bachelor's coefficient to Intercept and Ever Enrolled coefficient if low type. If high type also add Bachelor*High coefficient.

A.4 Indirect Inference: Targeted vs Simulated Moments

Table 22: Indirect Inference OLS Targets

	(1)	(2)	(3)	(4)
VARIABLES	Enrolled Data	Enrolled Sim	Continue Data	Continue Sim
Intercept	0.376	0.287	-0.068	-0.012
	(0.033)	(0.065)	(0.0502)	(0.032)
High Belief	0.215	0.201		
	(0.019)	(0.027)		
Fin Assist T2	0.150	0.154	0.072	0.075
	(0.024)	(0.027)	(0.034)	(0.009)
Fin Assist T3	0.297	0.301	0.095	0.135
	(0.026)	(0.035)	(0.0403)	(0.014)
First Gen	-0.129	-0.034		
	(0.021)	(0.017)		
Parent HSD			0.077	0.061
			(0.0390)	(0.021)
Parent SCOL			0.128	0.150
			(0.0379)	(0.028)
Parent Bach			0.216	0.235
	(0.031)	(0.015)	(0.0478)	(0.029)
White	0.116	0.067	0.015	0.034
	(0.026)	(0.038)	(0.036)	(0.018)
Hispanic	0.107	0.036	-0.016	0.018
	(0.031)	(0.045)	(0.044)	(0.021)
GPA Med			0.214	0.159
			(0.0348)	(0.015)
GPA High			0.3724	0.424
			(0.0371)	(0.025)

Table 22: Shows the exact moments targeted via indirect inference, the regression coefficients from Enrollment on the covariants and regression coefficients from Continuation on covariates. Columns 2 and 4 show the simulated moments as well as bootstrapped standard errors of the coefficients.

Table 23: Key Internal Parameter Results

Parameter	Description	Estimate
$\gamma_{p,0}$	Belief Constant	0.0057
		(0.0133)
$\gamma_{p,b}$	Belief: Meas Belief	0.88***
		(0.0103)
$\gamma_{p,h}$	Belief: P-Edu HSD	0.026**
		(0.0116)
$\gamma_{p,s}$	Belief: P-Edu SCOL	0.028***
		(0.0103)
$\gamma_{p,c}$	Belief: P-Edu Bach	0.055***
		(0.0102)
σ_p	Belief: Var Error	0.00018***
		(0.000043)
$\mu_{d,0}$	Non Pecun Util: Black 1st Gen Col Stud	-0.000056
		(0.000044)
$\mu_{d,C}$	Non Pecun Util: Col Edu Parents	0.00004
		(0.000037)
$\mu_{d,W}$	Non Pecun Util: White	0.000017
		(0.000028)
$\mu_{d,H}$	Non Pecun Util: Hispanic	0.000023
		(0.000034)
$\sigma_{d,1}$	Non Pecun Util Scale pd 1	0.000043
		(0.000066)
$\sigma_{d,2}$	Non Pecun Util Scale pd 2	0.000027
		(0.000066)
$\mu_c(\tau_h)$	Non Pecun Util high	0.00052***
		(0.000065)
$\mu_c(\tau_l)$	Non Pecun Util high	-0.0028***
		(0.00031)
$tuit_1$	Tuition Pd 1	\$7583.61***
		(120.5)
$tuit_2$	Tuiton Pd 2	\$6972.45***
		(16.05)

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 23: Shows the full list of 16 parameters estimated by indirect inference

A.5 Mismatch by Net Worth, Parental Edu, Race, and Ethnicity

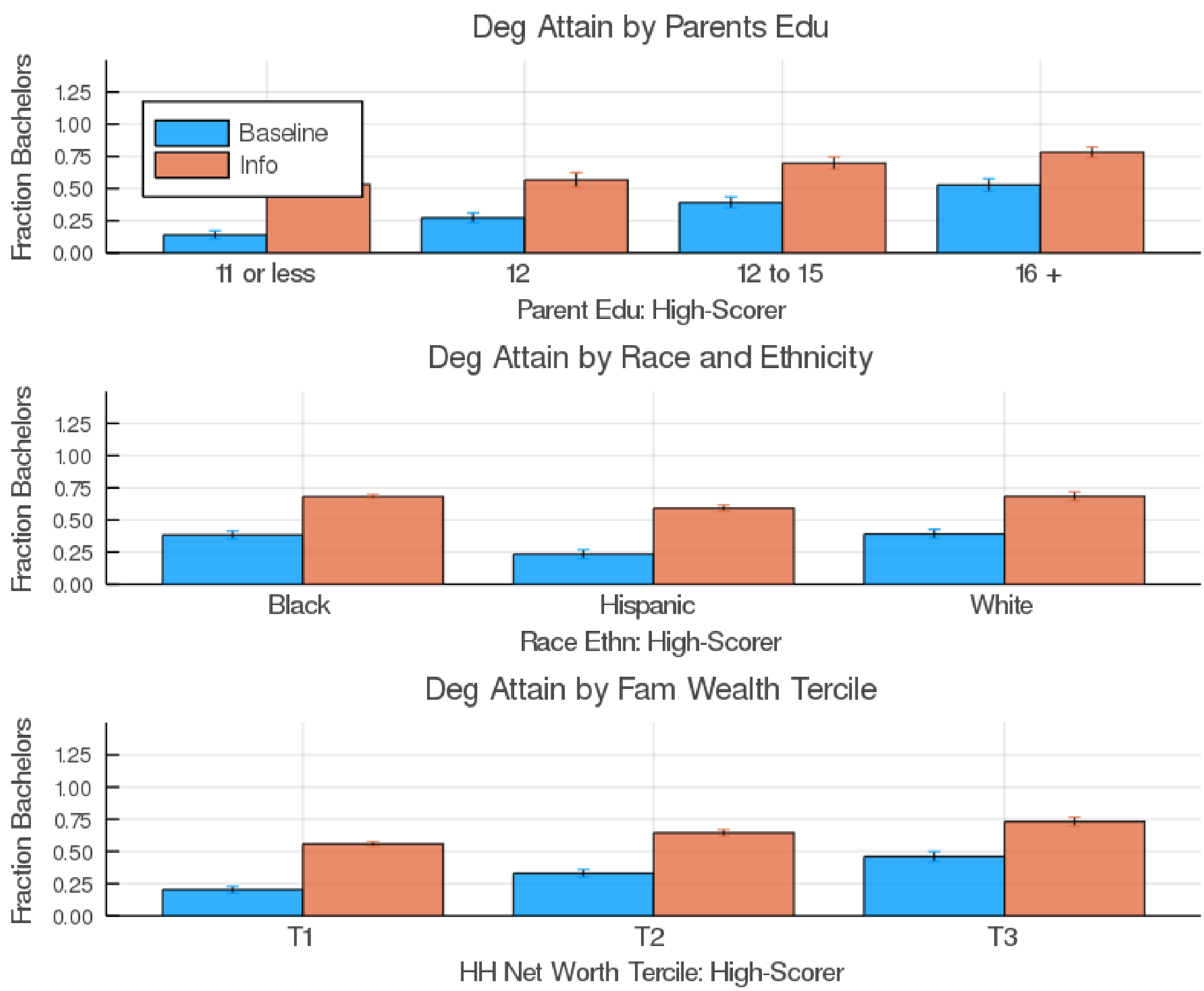

Figure 17: Shows difference in BA attainment under baseline model and under scenario where youth know their true type with certainty. This graph looks at predicted High Scorers by demographic group.

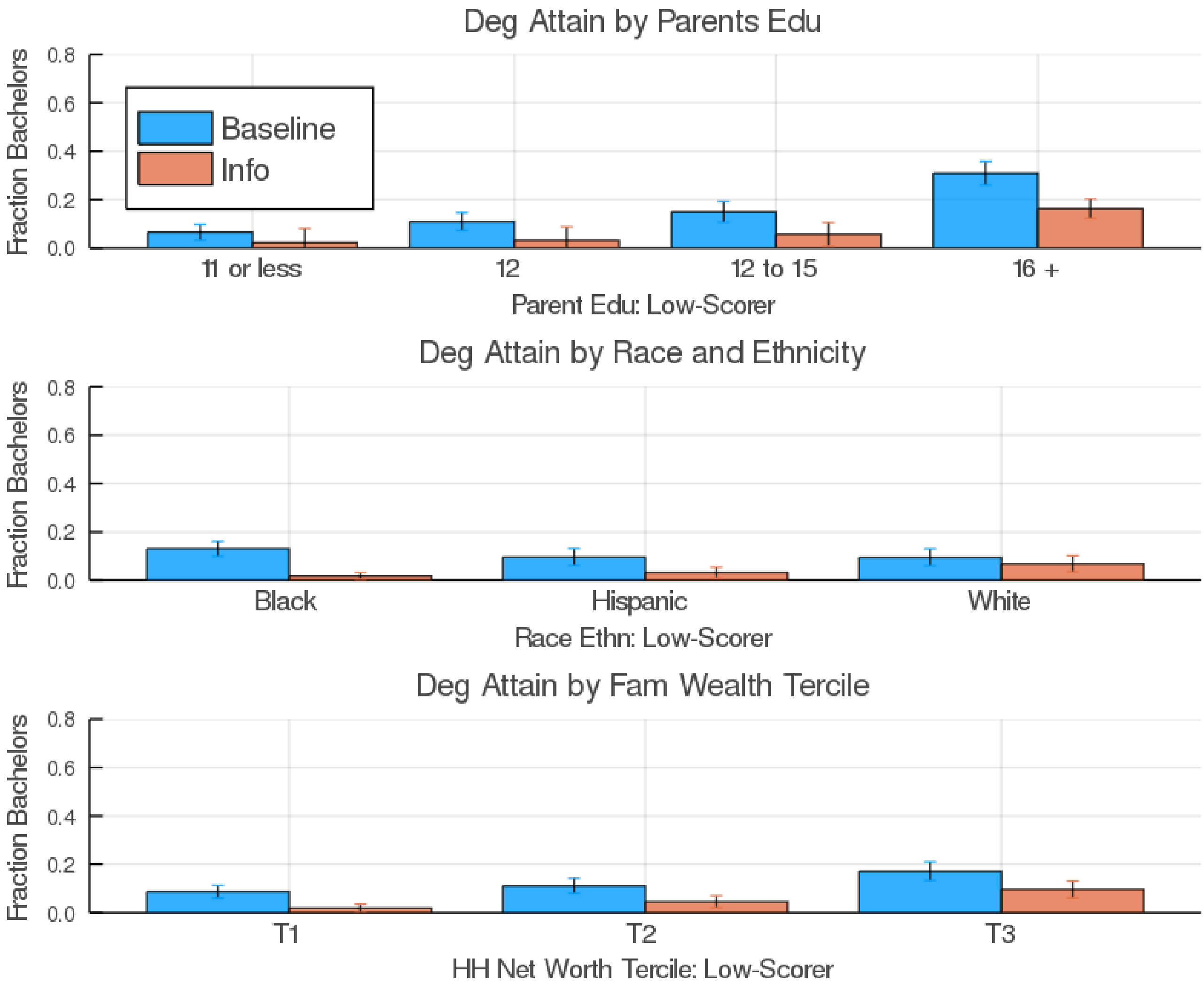

Figure 18: Shows difference in BA attainment under baseline model and under scenario where youth know their true type with certainty. This graph looks at predicted Lower Scorers by demographic group.

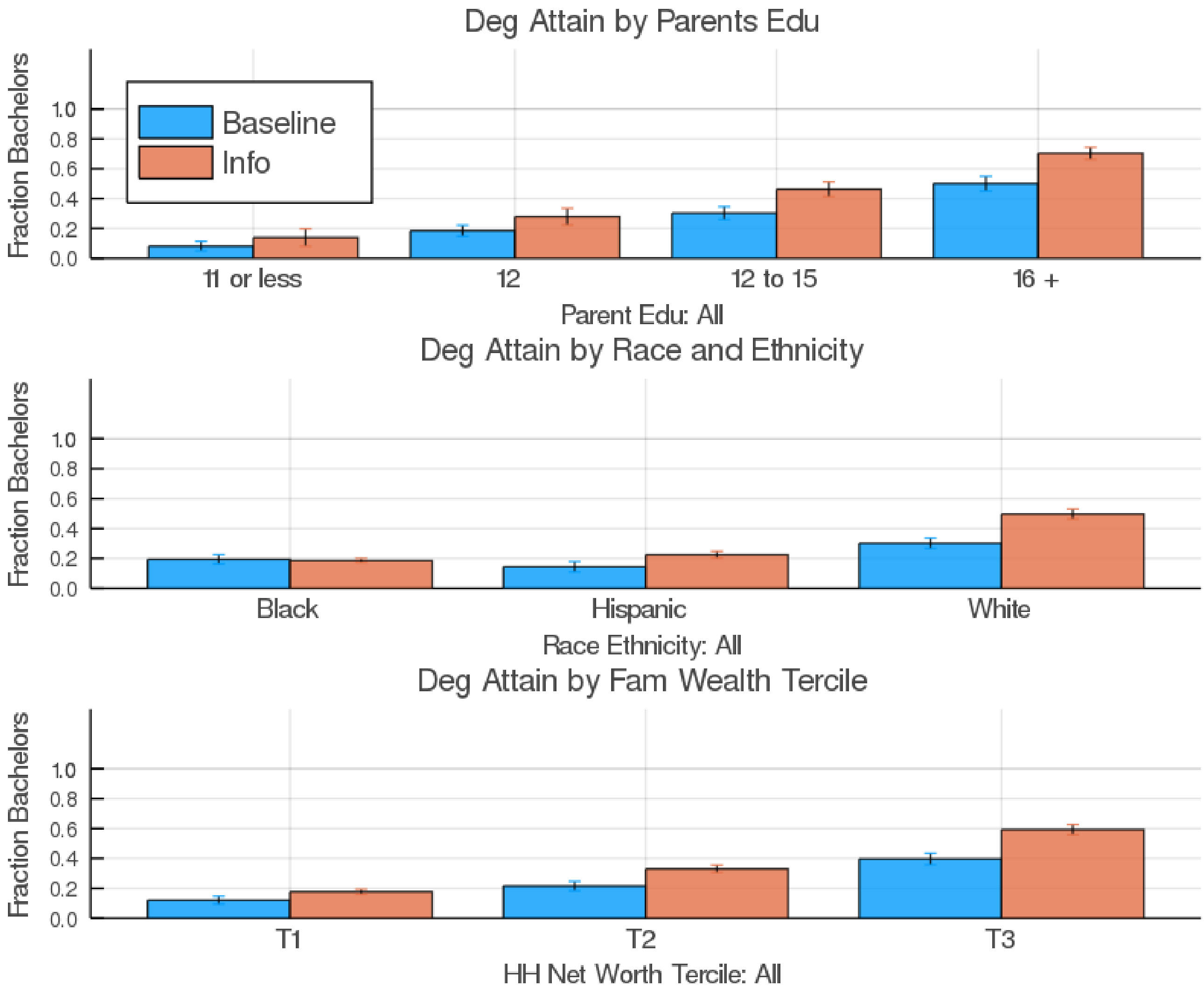

Figure 19: Shows difference in BA attainment under baseline model and under scenario where youth know their true type with certainty. This graph looks at all youth regardless of scoring type by demographic group.

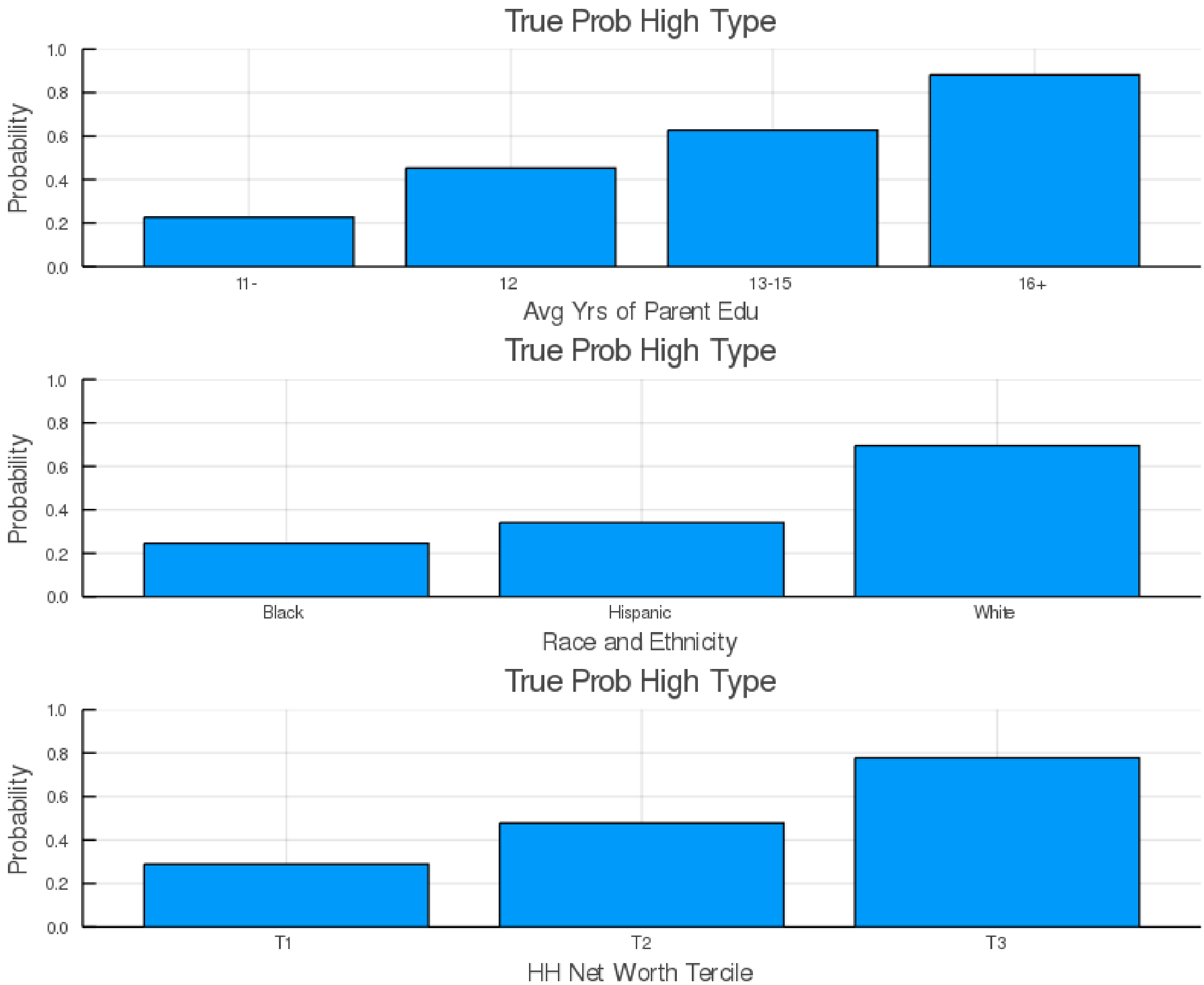

Figure 20: Shows the estimated fraction of high-scorers by demographic background from the finite mixture model.