Background, Beliefs and Economic Outcomes: How Family and Peers Relate to Beliefs, Early Pregnancy, Crime and Labor Market Outcomes

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Abstract

This dissertation consists of three chapters. The unifying theme of this thesis is how an adolescent's background is related to adolescent's beliefs about the future and how these beliefs are correlated with future outcomes. I then discuss what the policy implications are if beliefs with respect to ability or comparative advantage are biased.

The first chapter focuses on how beliefs are related to an adolescent's background using the NLSY97. Included in this chapter is an introduction to past work examining beliefs as well as a description of the dataset used for the remainder of the dissertation. The beliefs examined in this chapter are self reported beliefs of college enrollment, early pregnancy, arrests, becoming a victim of violence, working more than part time, and likelihood of serving in the military.

The second chapter then focuses on how beliefs are related to later life outcomes. Outcomes examined in this chapter are arrests, early pregnancy, service in the military, bachelor's degree attainment, and working more than an average of 20 hours per week in 2010. I then conclude the chapter with a discussion on rational expectations, where I distinguish between knowledge of outcomes and choices, versus knowledge of underlying ability or comparative advantage for different economic decisions.

The third chapter picks up on the discussion of rational expectations and explores an example, enrollment in college, of where beliefs about ability can be different than underlying ability. This chapter discusses the effect of these biases on inequality in bachelor's degree attainment and what the policy implications are of free college for all versus targeting subsidies and information to high ability youth from underrepresented backgrounds in higher education.

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Chapter 1

How are Peers and Parents Experiences Related to Beliefs about Future Outcomes?

1.1 Introduction

An adolescent's perception about the future can be influenced by the decisions and outcomes of parents and peers. For example youth from lower socioeconomic backgrounds can believe that positive outcomes like graduating college or working full time are less likely than youth from higher socioeconomic backgrounds. Likewise they may believe that negative outcomes like being a victim of violence, having an early pregnancy or being arrested are more likely than youth from higher socioeconomic backgrounds. This may be due to higher exposure to negative events and lower exposure to more positive events in the communities that lower socioeconomic status youth are raised in.

In this chapter I explore to what extent beliefs are correlated with the behavior of peers and the outcomes of parents. Specifically I will examine to what extent beliefs about outcomes and peers and parents experiences with similar outcomes are correlated. This is in order to examine if there is any evidence for social learning or imitation. In this paper I examine beliefs related to adverse outcomes: early pregnancy before age 20, arrests, and becoming a victim of violence. I will also examine beliefs related to labor market outcomes such as probability of enrolling in college, working full time, and likelihood of joining the military.

I will measure this by reporting the coefficients of peer and parental outcome covariates while controlling for household networth, measures of cognitive human capital and non cognitive human capital. The peer covariates that will be used are measures of peers that are members of clubs, members of gangs, have sex, and cut class. Parental outcome covariates include average parental education, parental incarceration history, parental military service, and mother's age at first birth. I find that parental education and peers college plans are strongly correlated with beliefs about going to college as well as working more than part time. Parental military service is also strongly correlated with likelihood of joining the military. Finally peers involvement in adverse behavior like being in a gang or cutting class is strongly associated with the beliefs about outcomes associated with own adverse behavior such as arrests, becoming a parent at a young age, and being a victim violence.

Then using a Oaxaca Blinder decomposition, I will also examine to what extent differences in peers behavior and parents outcomes explains differences by household net worth tercile in the measures of beliefs. In this analysis I find ...

Together this suggests that there is some evidence of social learning. if social learning determines beliefs that effect choices, then the extent to which this social learning reflects actual human capital suggests an inefficiency in the market that could be corrected by providing individuals more salient signals about their ability.

1.1.1 Contribution to the Literature

This paper is the first to analyze the relationship between peer behavior, parental outcomes and beliefs relating to adverse events and labor market outcomes. Much of the literature that has examined the relationship between beliefs and adolescent socioeconomic background has focused on beliefs about education outcomes, and education costs and benefits.

For instance Streufort 2000, argues that since youth from lower income backgrounds are more exposed to lower income adults, they will underestimate the returns to college. Consistent with this theory Horn, Chen, and Chapman 2000, found that students from lower income backgrounds overestimate the costs of attending college, which leads to lower perceived returns to college. Similarly Bleemer and Zafar 2018, find that youth from lower income and non college backgrounds exhibit more bias in the perceived net returns to college. Since expectations about education can be effected by social environment then its plausible that expectations about other outcomes can be influenced as well.

In a paper that is the most related to this one, researchers found that youth who exhibited more victimization shocks including being homeless, witnessing a shooting, or being a victim to a violent crime are less likely to believe they will earn a degree by age 30 and more likely to believe they will experience negative shocks like death, pregnancy, or arrests. Additionally adverse family shocks like divorce, death, unemployment and hospitalization where also highly negatively correlated with degree attainment expectations, and positively correlated with self reported probabilities of experiencing negative shocks (Deluca, Papageorge, Boselovic, Gehrshenson, Gray, Nerenberg, Sausedo,and Young 2021).

This paper contributes to this literature by showing results that suggests adolescents expectations about the future may also be affected by peers and outcomes for adults. It provides further evidence that more pessimism among lower socioeconomic status youth is explained by different levels of exposure to positive and adverse backgrounds. If these beliefs also affect the choices that adolescents make later in life, then understanding the social determinants of these beliefs may help policy makers identify populations of interests for information campaigns that improve later life outcomes.

1.2 Data and Summary Statistics

This section discusses the data set and the main variables that will be used in the analysis. For further information for how the sample was selected and how variables were defined see appendix A.1.

The data set that I use to examine how peers and parents activities are related to individual beliefs is the 1997 wave of the National Longitudinal Study of Youth (NLSY97). The NLSY97 is a panel data set that follows individuals from 1997 to the present day and is designed to be representative of youth born in the continental United States between 1980-1984. The study also over samples African Americans and Hispanic Americans.

The main analysis of interests is first to use Multivariate regression analysis to measure the effect of peers activities and parental outcomes on beliefs. Then the second analysis is to use a Oaxaca Blinder decomposition to measure how much socioeconomic differences in beliefs are explained by differences in peer composition and parental outcomes. In this analysis socioeconomic status is wealth measured by household net worth at the start of the survey.

The beliefs that I will use in this study are self reported probability about going to college in the future[1], self reported probability of working more than 20 hours in the future[2], likelihood on a scale of 1-5 of joining the military, self reported probability of having child within the next year, self reported probability of being arrested in the next year, and self reported probability of becoming a victim of violence next year[3]. All of the beliefs used in this study are beliefs recorded for survey years where agents were 18 or younger.

Peer measures used are respondent reports of percent of kids in respondents grade that belonged to a gang, had college plans, had sex, cut class, and were members of sports, clubs or extracurricular activities. The peer variables are measured on a scale of 1-5 where each unit increase corresponds to approximately a 25 percent increase of peers with the reported characteristic.

Parent outcome measures are average years of parents schooling, mother's age at first birth, and indicators for whether parents served in the military or were incarcerated. Socioeconomic status is measured by the corresponding wealth tercile of household net worth.

In the analysis I control for cognitive human capital measured by ASVAB AFQT score, which is the respondent's percentile for their math and verbal scores for the ASVAB battery of exams. I also control for non cognitive ability by using indicators for whether respondent's had sex by age 15, stole more than $50 by age 18, intentionally attacked or harmed someone by age 18.

[1] Since different year of birth cohorts were asked different questions this uses, probability of having a degree, probability of being enrolled in school next year, probability of being enrolled in school in five years

[2] For cohort born before 1982, this is probability of working 20 plus hours at age 30, and for cohorts born in 1982 or later this is probability of working 20 plus hours in five years.

[3] With the exception of likelihood of joining the military, beliefs measured in 1997 are used for cohorts born before 1982, and for the other cohorts beliefs measured 2000 are used

Table 1.1: Summary Statistics: Beliefs, Peer, and Parent Measurs by Net Worth

VARIABLES	All	Low Net Worth	Mid Net Worth	High Net Worth
Belief: Prob Enroll Coll	71.17	63.42	71.30	82.67
Belief: Prob Work 20+ Hrs in Future	93.64	92.09	93.82	95.78
Belief: Prob Arrested Next Year	10.07	11.93	9.469	7.973
Belief: Prob Victim Violence Next Year	13.25	14.91	12.74	11.35
Belief: Prob Parent Next Year	6.882	9.088	6.667	3.778
Belief: Likelihood Join Military	2.196	2.339	2.176	2.032
Avg Years of Parents Schooling	12.54	11.54	12.52	14.10
Parent Ever in Jail	0.0668	0.111	0.0495	0.0209
Parent Serve in Military	0.252	0.219	0.270	0.281
Mom's Age at First Birth	22.69	21.27	22.36	25.26
HH Net Worth ($1000s)	139.5	9.578	105.2	381.1
Pct Peers had Sex	0.211	0.222	0.226	0.174
Pct Peers in Gang	0.177	0.228	0.170	0.108
Pct Peers College Plans	0.635	0.588	0.634	0.708
Pct Peers in Clubs/Sports	0.664	0.646	0.663	0.694
Pct Peers Cut Class	0.363	0.402	0.360	0.306
ASVAB AFQT (Pctile Math/Verbal Tests)	45.84	33.21	45.55	65.53
Ever Stole $50+ by age 18	0.139	0.158	0.137	0.112
Ever Attack/harm Someone by age 18	0.301	0.371	0.311	0.181
Ever had Sex by age 15	0.370	0.471	0.380	0.204
Female	0.520	0.559	0.489	0.497
Hispanic	0.205	0.292	0.198	0.0803
Black	0.273	0.399	0.276	0.0782
Sample Size	4,702	1,903	1,554	1,245

I drop respondents who are missing data for all of the covariates with the exception of belief about college enrollment and likelihood of military service, since only a subset of respondents have this information available. I also keep respondents if they identify as White Non Hispanic, Black of any ethnicity, and Hispanic, since other racial/ethnic groups have very small sample sizes.

Summary Statistics for the sample are shown in Table 1.1. The bottom wealth tercile slightly oversamples women, and the share that are Black or Hispanic declines with increasing wealth terciles. The table shows that youth from a lower wealth tercile are on average more pessimistic about college enrollment and working more than part time. Youth from a lower wealth tercile also believe that they are more likely to have a child within a year, join the military, be a victim of violence, or be arrested.

Peer measures exhibit a similar trend, where more negative social attributes are more common in lower net worth terciles and more positive attributes are less common in lower net worth terciles. For instance compared to youth from the top net worth tercile, youth from the lower net worth terciles have more peers who have had sex, who are involved in gangs, and cut class. They also have less peers with college plans and that are involved in extracurricular activities.

Lower net worth tercile youth also have parents with less years of schooling, younger mother's age at first birth, and higher proportion of parents who have been incarcerated. Parental service in the military increases with wealth tercile as well. They also have lower measures of cognitive and non cognitive human capital.

In summary youth from lower socioeconomic backgrounds not only have lower measures of human capital on average but have peer and parental backgrounds with less socially positive attributes and more socially negative attributes. In the next section I investigate to what extent peer and parental measures are correlated with beliefs while controlling for differences in human capital measures.

1.3 Analysis

In this section I first examine in section 1.3.1 the correlation between peers and parent characteristics with beliefs about school, education, military service, becoming a parent at a young age, being arrested, or becoming a victim of violence. I report these correlations throught the coefficients from ordinary least squares regressions

Then I examine in section 1.3.2 to what extent differences in average peer and parental characteristics by household net worth tercile can explain socioeconomic gaps in beliefs as shown in the summary statistics in Table 1.1. In this section these results will be reported using a Oaxaca Blinder decomposition on beliefs.

Of specific interest is a social learning or social modeling mechanism, which, proposes that agents gain information from peers and important adults in their lives about what activities they have a competitive advantage in or will simply enjoy. This will be captured by the coefficient for similar behavior from peers and parents as the belief in question.

1.3.1 Multivariate Regression Analysis: Beliefs, Peers, and Parents

In this section we explore to what extent peer and parent attributes are associated with beliefs about labor market, schooling, arrest, pregnancy at young ages, and becoming a victim of violence. The results are presented through regression covariates using Ordinary Least Squares of a model for each j type of belief as given below.

$$\vec{Belief}_{i,j} = \gamma_{\vec{par},j}\vec{Parent}_i + \gamma_{\vec{peer},j}\vec{Peer}_i + \vec{\beta}\vec{X_{i,j}} + \vec{\varepsilon_{i,j}} \tag{1.1}$$

In equation 1.1 above, the subscript j represents the specific belief examined, while subscript i represents the individual respondent to the Survey. The vector $\vec{Parent}_i$ is the vector of parents outcomes including average years of schooling, mother's age at first birth, and indicators for if parents had ever been incarcerated or served in the military. The vector $\vec{Peer}_i$ is the vector of covariates for percent of peers engaged in different behavior including plans for college, cutting class, involved in sports or clubs, or in gangs. Additionally X_i is a vector of controls including household net worth, cognitive and non cognitive human capital measures, census region at the start of the survey, urban rural status at the start of the survey, sex, race and ethnicity. The parameters of interest are $\gamma_{par,j}$ and $\gamma_{peer,j}$ which represents the relationship between peers and parents experiences to beliefs.

What is of specific interest in this paper are the coefficients for parent outcomes and peer measures that are of the similar activities of the beliefs. For example, when regressing beliefs about college degree, what is of first most importance are the coefficients on average years of parent's schooling and peers who plan to go to college. Similarly when regressing probability of arrest or victim of violence, what is of interest is the coefficient on parental incarceration history and percent of peers in gangs or who cut class, since adverse behavior and crime are likely correlated with arrest and becoming victims of violence.

The results for labor market and schooling beliefs are shown in Table 1.2. Table 1.2 shows that parental education is strongly positively correlated with self reported probability of enrolling in college and for working more than 20 hours a week in the future. First of all the table shows that human capital measures are strongly correlated with belief measures. Where higher measures of cognitive ability and non cognitive ability are associated with higher likelihoods of going to college and lower likelihoods of joining the military. For probability of working more than 20 hours there is a positive relationship with cognitive human capital through ASVAB AFQT.

Table 1.2 shows that for beliefs about the military and going to college, parents having similar experiences is associated with a higher reported likelihood. For instance column 1 shows that holding all else equal a one year increase in average parents years of schooling is associated with a 2.12 percentage point increase in self reported probability of going to college. This amount is similar to a 10 percentile increase in ASVAB AFQT or nearly $300,000 increase in household net worth.Similarly having parents who served in the military is associated with ranking the likelihood of joining the military 0.15 points higher on the 1-5 likelihood scale. This is roughly the same as 40 percentile point drop on the ASVAB AFQT.

Additionally for beliefs about going to college similar peer plans is also strongly correlated with beliefs. For instance holding all else equal if percentage of peers with college plans increases by 25 percentage points, then self reported probability of going to college increase by about 4.5 percentage points which is close to a 17 percentile increase in ASVAB AFQT.

Percent of peers with college plans and average years of parents schooling is also strongly positively correlated with self reported probability of working more than 20 hours. Mother's age at first birth is also positively correlated with probability of enrolling in college and negatively correlated with likelihood of joining the military.

Table 1.2: OLS Results: Beliefs about School and Labor Market

VARIABLES	(1) Prob Enroll Coll	(2) Prob Work 20+ Hrs	(3) Likelihood Military
Avg Years of Parents Schooling	2.1225***	0.2802**	-0.0208*
	(0.2695)	(0.1389)	(0.0112)
Parent Ever in Jail	-4.1354*	-0.2917	0.0797
	(2.1924)	(1.1686)	(0.0899)
Parent Serve in Military	-0.0145	0.4520	0.1496***
	(1.0815)	(0.5031)	(0.0455)
Mom's Age at First Birth	0.2767**	0.0737	-0.0137***
	(0.1091)	(0.0605)	(0.0046)
% Peers Coll Plan ($\sim$ 25 ppts)	4.4594***	0.8037***	0.0041
	(0.5228)	(0.2856)	(0.0212)
% Peers Cut Class ($\sim$ 25 ppts)	-0.7229	0.1863	0.0074
	(0.4534)	(0.2180)	(0.0185)
% Peers Club/Sports ($\sim$ 25 ppts)	0.6083	-0.0120	0.0155
	(0.5107)	(0.2635)	(0.0202)
% Peers in Gang ($\sim$ 25 ppts)	0.2199	-0.5441	0.0329
	(0.6398)	(0.3352)	(0.0255)
ASVAB AFQT (10 percentile pts)	2.5655***	0.7581***	-0.0347***
	(0.2074)	(0.1114)	(0.0087)
Ever Stole $50+ by age 18	-4.5498***	-0.7274	0.0205
	(1.6153)	(0.8229)	(0.0622)
Ever Attack Someone by age 18	-4.0493***	0.7044	0.1944***
	(1.1894)	(0.5846)	(0.0486)
Ever had Sex by age 15	-4.8054***	0.9772*	0.0499
	(1.1474)	(0.5774)	(0.0466)
HH Net Worth ($10,000s)	0.0737***	-0.0201	-0.0015
	(0.0247)	(0.0139)	(0.0010)
Observations	4,172	4,702	4,018
R-squared	0.2489	0.0383	0.0733
Census Region & Urban Rural	Yes	Yes	Yes
Year of Birth Fixed Effect	Yes	Yes	Yes
Race, Ethnicity, Gender	Yes	Yes	Yes

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

Table 1.3: OLS Results: Beliefs about Adverse Events, Early Pregnancy

VARIABLES	(1) Prob Victim	(2) Prob Arrest NY	(3) Prob Parent NY	(4) Prob Parent NY
Avg Years of Parents Schooling	-0.0908	0.1596	-0.1212	-0.1582
	(0.1733)	(0.1452)	(0.1398)	(0.2096)
Parent Ever in Jail	1.8175	2.3917*	2.0023	2.0749
	(1.3289)	(1.2722)	(1.2632)	(1.9557)
Parent Serve in Military	0.0669	0.3959	-0.2839	0.0852
	(0.6541)	(0.5841)	(0.5154)	(0.8121)
Mom's Age at First Birth	-0.0544	-0.0522	-0.0810	-0.1335
	(0.0664)	(0.0600)	(0.0549)	(0.0841)
% Peers Coll Plan ($\sim$ 25 ppts)	-0.0754	-0.2675	-0.1264	-0.0924
	(0.3048)	(0.2725)	(0.2662)	(0.4278)
% Peers Cut Class ($\sim$ 25 ppts)	1.0273***	0.8825***	0.4485*	0.3756
	(0.2771)	(0.2361)	(0.2430)	(0.3656)
% Peers Clubs Sports ($\sim$ 25 ppts)	-0.7796**	-0.2447	-0.4251	-0.1213
	(0.3041)	(0.2652)	(0.2767)	(0.4117)
% Peers in Gang ($\sim$ 25 ppts)	0.9426**	0.9385***	1.1489***	1.3210**
	(0.3872)	(0.3458)	(0.3699)	(0.5439)
% Peers had Sex ($\sim$ 25 ppts)				0.2317
				(0.4222)
ASVAB AFQT (10 percentile pts)	0.8050***	-0.1415	-0.3452***	-0.4522***
	(0.1241)	(0.1072)	(0.1001)	(0.1664)
Ever Stole $50+ by age 18	4.2289***	6.9152***	3.4724***	3.7959***
	(1.0287)	(1.0243)	(0.9330)	(1.4613)
Ever Attack Someone by age 18	3.9065***	3.6865***	2.3279***	3.0223***
	(0.7345)	(0.6351)	(0.6348)	(1.0385)
Ever had Sex by age 15	2.4250***	3.5360***	5.7168***	5.1619***
	(0.6799)	(0.5933)	(0.5777)	(0.9358)
HH Net Worth ($10,000s)	-0.0424***	0.0004	0.0075	0.0296
	(0.0156)	(0.0145)	(0.0107)	(0.0195)
Observations	4,702	4,702	4,702	2,094
R-squared	0.0581	0.1216	0.1177	0.1231
Census Region & Urban Rural	Yes	Yes	Yes	Yes
Year of Birth Fixed Effect	Yes	Yes	Yes	Yes
Gender, Race, Ethnicity	Yes	Yes	Yes	Yes

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

Table 1.3 shows the results for beliefs about early pregnancy and adverse events like arrest or becoming a victim of violence. Table 1.3 has two specifications for Probability of being a Parent NY that does and does not include percent of peers who have had sex, which was non missing only for the cohort born before 1982. For these measures of beliefs there is a negative correlation between cognitive and non cognitive ability. Household net worth also only explains.

Some similar patterns emerge from Table 1.3. There is some evidence of social learning or patterning since parental incarceration history is marginally positively correlated with self reported probability of arrest. However mother's age at first birth does not have a statistically significant effect on probability of being a parent. More peers involved in adverse behavior like cut class and being in a gang are positively associated with self reported beliefs of being a victim of violence, arrested in the next year or being a parent young. Interestingly number of peers who had sex is not statistically significant for probability of being a parent next year.

In summary there is some evidence of social learning or modeling, where more educated parents and more peers with college plans is associated with more optimism about obtaining a degree. To the extent that higher education is correlated with higher likelihood of working more than part time, then this holds for self reported probability of working more than 20 hours a week. I also found that Parents with a military history and incarceration history are positively associated with joining the military and probability of being arrested respectively.

Similarly more peers involved in more adverse behavior is also associated with higher self reported likelihoods of becoming a parent within the next year or experiencing a negative event like becoming a victim of violence or being arrested. Two events that are associated with crime participation. These relationships hold even when controlling for household net worth, gender, race, ethnicity, and human capital measures.

In the next section I examine to what extent differences in peer and parent measures explain differences in beliefs by household net worth tercile. Where youth from lower socioeconomic backgrounds exhibit more pessimism regarding positive social outcomes like education and working more than part time and think that early pregnancy and negative events are more likely.

1.3.2 Oaxaca Blinder Decomposition: What Explains Belief Gaps

In this subsection I focus on gaps in beliefs by household net worth or wealth, which is the measure of socioeconomic status used in this paper. Specifically I will use a Oaxaca Blinder decomposition to estimate how much household net worth group differences in average parent outcomes and peer experiences can explain differences in beliefs.

The Oaxaca Blinder decomposition is designed to decompose differences in group averages by an explained portion which is differences in covariate averages, and an unexplained portion which is differences in the coefficients on covariates from

OLS regressions carried out separately by group (Oaxaca, 1973; Blinder, 1973). The unexplained portion on certain covariates like race and sex, have often been interpreted as evidence of direct discrimination.

In this paper I will focus only on the explained portion, since the main question of interest concerns how similar outcomes and experiences by peers and adults affect beliefs. This paper will not take attempt to provide a measure of discrimination and will leave it to future work to explore. It is important to point out that discrimination in housing, schooling and law enforcement may lead to different covariate averages in parent and peer outcomes. In this case discrimination may play an important role in the explained portion.

This paper will also leave discussions for differences in social learning by group for future work as well, since for now we are concerned if there is any evidence for social learning not just by any one group. For more information on the specific components of the unexplained portion relating to peer and parent covariates see the Blinder Oaxaca output in Appendix A.2.1.

Table 1.4: Pct Explained vs High Net Worth: School, Military, Work Beliefs

Beliefs	Coll	Coll	Work 20+ hrs	Work 20+ hrs	Military	Military
Net Worth	Low	Mid	Low	Mid	Low	Mid
Parent Covariates	47.28	44.12	32.46	50.24	30.79	25.72
Avg Yrs Parents School	39.7***	34.25***	13.82	34.15	16.17	10.52
Parent in Jail	3.86**	0.3	2.01	-2.48	1.61	0.57
Parent Serve Military	0.22	-0.04	2.51*	0.15	-4.08**	-0.07
Mom's Age First Birth	3.5	9.61**	14.12	18.42	17.1**	14.7**
Peer Covariates	18.75	16.23	23.95	34.35	2.54	5.15
% Peers Coll Plan	17.14***	11.94**	9.51	24.55***	-0.86	-0.25
% Peers Cut Class	1.5	1.49	-0.44	-5.49	1.15	1.07
% Peers Club/Sports	0.49	1.9*	2.42	5.6	-1.65	-1.32
% Peers in Gang	-0.38	0.9	12.46	9.69	3.9	5.65
Total Difference	19.27***	11.33***	3.7***	1.86***	0.3***	0.14***
Total Explained	13.45***	9.54***	3.04***	1.22**	0.28***	0.22***

Hypothesis tests if explained portion equals zero, statistics are covariate explained portion divided by total explained
*** p<0.01, ** p<0.05, * p<0.1

Table 1.5: Pct Explained vs High Net Worth: Arrest, Victim, Pregnant Beliefs

Beliefs	Arrest	Arrest	Victim	Victim	Pregnancy	Pregnancy
Net Worth Tercile	Low	Mid	Low	Mid	Low	Mid
Parent Covariates	-14.24	13.25	48.98	83.68	20.04	8.31
Avg Yrs Parents School	-21.12	-31.20	4.88	48.12	13.88	-5.26
Parent Jail	10.26*	-1.57	13.31	7.83	2.47	1.75
Parent Military	0.11	-0.97	0.0	-0.68	0.512	0.05
Mom's Age First Birth	-3.49	47**	30.80	28.41	3.18	11.77*
Peer Covariates	50.85	25.42	92.09	135.44	18.82	15.75
% Peers Coll Plan	7.41	-3.85	12	-42.03	-0.33	3.81
% Peers Cut Class	16.98***	18.6**	35.22***	66.34**	5.28**	4.26
% Peers Club/Sports	0.11	5.99	5.2	46.94**	1.85	0.41
% Peers in Gang	26.35***	4.7	39.66**	64.19	12.03***	7.27
Total Difference	3.99***	2.01***	3.55***	1.42***	5.29***	2.91***
Total Explained	2.52***	0.98	1.47	0.32	5.94***	2.36***

Hypothesis tests if explained portion equals zero, statistics are covariate explained portion divided by total explained
*** p<0.01, ** p<0.05, * p<0.1

1.4 Conclusion

Chapter 2

How do Beliefs about Future Outcomes relate to Actual Outcomes?

2.1 Introduction

2.2 Data and Summary Statistics

This section discusses the data set and the main variables that will be used in the analysis. For further information for how the sample was selected and how variables were defined see appendix A.1.

The data set that I use to examine how peers and parents activities are related to individual beliefs is the 1997 wave of the National Longitudinal Study of Youth (NLSY97). The NLSY97 is a panel data set that follows individuals from 1997 to the present day and is designed to be representative of youth born in the continental United States between 1980-1984. The study also over samples African Americans and Hispanic Americans.

The main analysis of interests is first to use Multivariate regression analysis to measure the effect of peers activities and parental outcomes on beliefs. Then the second analysis is to use a Oaxaca Blinder decomposition to measure how much socioeconomic differences in beliefs are explained by differences in peer composition and parental outcomes. In this analysis socioeconomic status is wealth measured by household net worth at the start of the survey.

The beliefs that I will use in this study are self reported probability about going to college in the future[1], self reported probability of working more than 20 hours in the future[2], likelihood on a scale of 1-5 of joining the military, self reported probability

[1]Since different year of birth cohorts were asked different questions this uses, probability of having a degree, probability of being enrolled in school next year, probability of being enrolled in school in five years

[2]For cohort born before 1982, this is probability of working 20 plus hours at age 30, and for cohorts born in 1982 or later this is probability of working 20 plus hours in five years.

of having child within the next year, self reported probability of being arrested in the next year, and self reported probability of becoming a victim of violence next year[3]. All of the beliefs used in this study are beliefs recorded for survey years where agents were 18 or younger.

Peer measures used are respondent reports of percent of kids in respondents grade that belonged to a gang, had college plans, had sex, cut class, and were members of sports, clubs or extracurricular activities. The peer variables are measured on a scale of 1-5 where each unit increase corresponds to approximately a 25 percent increase of peers with the reported characteristic.

Parent outcome measures are average years of parents schooling, mother's age at first birth, and indicators for whether parents served in the military or were incarcerated. Socioeconomic status is measured by the corresponding wealth tercile of household net worth.

In the analysis I control for cognitive human capital measured by ASVAB AFQT score, which is the respondent's percentile for their math and verbal scores for the ASVAB battery of exams. I also control for non cognitive ability by using indicators for whether respondent's had sex by age 15, stole more than $50 by age 18, intentionally attacked or harmed someone by age 18.

Summary Statistics for the sample are shown in Table 1.1. The bottom wealth tercile slightly oversamples women, and the share that are Black or Hispanic declines with increasing wealth terciles. The table shows that youth from a lower wealth tercile are on average more pessimistic about college enrollment and working more than part time. Youth from a lower wealth tercile also believe that they are more likely to have a child within a year, join the military, be a victim of violence, or be arrested.

[3]With the exception of likelihood of joining the military, beliefs measured in 1997 are used for cohorts born before 1982, and for the other cohorts beliefs measured 2000 are used

Table 2.1: Summary Statistics: Outcomes and Beliefs by Net Worth

VARIABLES	All	Low Net Worth	Mid Net Worth	High Net Worth
Bachelor's or Higher	0.0961	0.0447	0.0849	0.189
Work Avg 20 hours in 2010	0.695	0.615	0.714	0.791
Ever Served in Armed Forces	0.0630	0.0468	0.0811	0.0651
Had Children by age 20	0.180	0.274	0.169	0.0506
Been Arrested	0.349	0.400	0.354	0.263
Been Incarcerated	0.0887	0.114	0.0907	0.0482
Belief: Prob Enroll Coll	71.17	63.42	71.30	82.67
Belief: Prob Work 20+ Hrs	93.64	92.09	93.82	95.78
Belief: Prob Arrested	10.07	11.93	9.469	7.973
Belief: Prob Victim Violence	13.25	14.91	12.74	11.35
Belief: Prob Parent Young	6.882	9.088	6.667	3.778
Belief: Likelihood Join Military	2.196	2.339	2.176	2.032
ASVAB AFQT	45.84	33.21	45.55	65.53
Ever Stole $50+ by age 18	0.139	0.158	0.137	0.112
Ever Attack/harm Someone by age 18	0.301	0.371	0.311	0.181
Ever had Sex by age 15	0.370	0.471	0.380	0.204
Sample Size	4,702	1,903	1,554	1,245

Peer measures exhibit a similar trend, where more negative social attributes are more common in lower net worth terciles and more positive attributes are less common in lower net worth terciles. For instance compared to youth from the top net worth tercile, youth from the lower net worth terciles have more peers who have had sex, who are involved in gangs, and cut class. They also have less peers with college plans and that are involved in extracurricular activities.

Lower net worth tercile youth also have parents with less years of schooling, younger mother's age at first birth, and higher proportion of parents who have been incarcerated. Parental service in the military increases with wealth tercile as well. They also have lower measures of cognitive and non cognitive human capital.

In summary youth from lower socioeconomic backgrounds not only have lower measures of human capital on average but have peer and parental backgrounds with less socially positive attributes and more socially negative attributes. In the next section I explore to what extent peer and parental measures are correlated with beliefs while controlling for differences in human capital measures.

2.3 Analysis

2.3.1 Multivariate Regression Analysis: Beliefs and Outcomes

Table 2.2: OLS Results: School and Labor Market Outcomes

VARIABLES	(1) Col_Grad_30	(2) Work Avg 20 hours in 2010	(3) Ever Served in Armed Forces
Belief: Prob Enroll Coll	0.0189***	0.0073***	0.0006
	(0.0017)	(0.0024)	(0.0013)
Belief: Prob Work 20+ Hrs	-0.0016	0.0137***	0.0003
	(0.0032)	(0.0047)	(0.0024)
Belief: Prob Arrest NY	-0.0013	-0.0056	-0.0028
	(0.0033)	(0.0049)	(0.0025)
Belief: Prob Victim Violence	-0.0054*	0.0043	-0.0007
	(0.0031)	(0.0041)	(0.0022)
Belief: Prob Parent Young	0.0067**	0.0102**	-0.0021
	(0.0032)	(0.0048)	(0.0029)
Likelihood Military, Unlikely			0.0060
			(0.0101)
Likelihood Military, Undecided			0.0340***
			(0.0107)
Likelihood Military, Likely			0.0690***
			(0.0194)
Likelihood Military, Very Likely			0.1162***
			(0.0242)
Avg Years Parents School	0.0330***	0.0047	0.0010
	(0.0036)	(0.0041)	(0.0023)
HH Net Worth ($10,000s)	0.0026***	0.0007*	-0.0002
	(0.0004)	(0.0004)	(0.0002)
Parent Ever in Jail	-0.0030	-0.0393	-0.0093
	(0.0210)	(0.0306)	(0.0162)
Parent Serve in Military	-0.0427***	-0.0135	0.0566***
	(0.0139)	(0.0162)	(0.0111)
Mom's Age at First Birth	0.0046***	0.0015	-0.0014
	(0.0014)	(0.0017)	(0.0009)
ASVAB AFQT (10 percentile pts)	0.0492***	0.0160***	0.0098***
	(0.0028)	(0.0032)	(0.0019)
Ever Stole $50+ by age 18	-0.0363**	-0.0127	-0.0134
	(0.0163)	(0.0225)	(0.0133)
Ever Attack Someone by age 18	-0.0634***	-0.0374**	0.0148
	(0.0131)	(0.0176)	(0.0108)
Ever had Sex by age 15	-0.0776***	-0.0671***	0.0103
	(0.0132)	(0.0169)	(0.0104)
Observations	4,172	4,172	3,583
R-squared	0.3505	0.0668	0.0659
Census Region & Urban Rural	Yes	Yes	Yes
Year of Birth	Yes	Yes	Yes
Gender, Race, Ethnicity	Yes	Yes	Yes
Primary School Peers	Yes	Yes	Yes

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

Table 2.3: OLS Results: Early Pregnancy, Arrest and Incarceration

VARIABLES	(1) Been Arrested	(2) Been Incarcerated	(3) Had Children by age 20
Belief: Prob Enroll Coll	-0.0092***	-0.0033**	-0.0072***
	(0.0023)	(0.0015)	(0.0020)
Belief: Prob Work 20+ Hrs	-0.0001	0.0045	-0.0046
	(0.0042)	(0.0028)	(0.0040)
Belief: Prob Arrest NY	0.0205***	0.0083**	-0.0029
	(0.0046)	(0.0039)	(0.0043)
Belief: Prob Victim Violence	-0.0001	-0.0014	-0.0007
	(0.0037)	(0.0028)	(0.0035)
Belief: Prob Parent Young	0.0111**	0.0084**	0.0117**
	(0.0045)	(0.0038)	(0.0047)
Avg Years Parents School	-0.0062	-0.0051**	-0.0107***
	(0.0039)	(0.0025)	(0.0032)
HH Net Worth ($10,000s)	-0.0003	-0.0001	-0.0005**
	(0.0004)	(0.0003)	(0.0002)
Parent Ever in Jail	0.0654**	0.0794***	0.0668**
	(0.0283)	(0.0227)	(0.0273)
Parent Serve in Military	0.0160	0.0032	-0.0204*
	(0.0150)	(0.0095)	(0.0116)
Mom's Age at First Birth	0.0001	-0.0001	-0.0045***
	(0.0015)	(0.0010)	(0.0013)
ASVAB AFQT (10 percentile pts)	-0.0068**	-0.0065***	-0.0077***
	(0.0030)	(0.0019)	(0.0023)
Ever Stole $50+ by age 18	0.2275***	0.1173***	0.0060
	(0.0221)	(0.0187)	(0.0187)
Ever Attack Someone by age 18	0.1640***	0.0451***	0.0338**
	(0.0177)	(0.0114)	(0.0141)
Ever had Sex by age 15	0.1604***	0.0437***	0.1365***
	(0.0166)	(0.0103)	(0.0142)
Observations	4,172	4,172	4,172
R-squared	0.2411	0.1280	0.1800
Census Region & Urban Rural	Yes	Yes	Yes
Year of Birth	Yes	Yes	Yes
Gender, Race, Ethnicity	Yes	Yes	Yes
Primary School Peers	Yes	Yes	Yes

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

2.3.2 Oaxaca Blinder: How much do Beliefs Explain?

Table 2.4: Percent Explained vs High Net Worth: School, Military, Work Outcomes

Outcome	Coll	Coll	Work 20+ hrs	Work 20+ hrs	Military	Military
Net Worth	Low	Mid	Low	Mid	Low	Mid
Beliefs	10.38	11.94	6.61	16.89	37.5	15.73
Prob College	10.78***	11.98***	7.36	16.89***	-25	-1.69
Prob Work 20+ hrs	-0.12	-0.08	4.71***	1.2	-4.69	0.0
Prob Arrest Next Year	0.18	-0.28	0.74	2.13	-31.25*	-0.56
Prob Victim Next Year	0.95**	0.28	0.37	-1.6	9.37	0.56
Prob Pregnant Next Year	-1.42**	-0.03	-0.04**	-1.73	-4.69	10.11
Likelihood Military					93.75***	-24.16**
Total Difference	0.4109***	0.2808***	0.1601***	0.0730***	0.0236***	0.0142
Total Explained	0.3246***	0.2462***	0.1210***	0.0752***	-0.0064	0.0178*

Hypothesis tests if explained portion equals zero, statistics are covariate explained portion divided by total explained
*** p<0.01, ** p<0.05, * p<0.1

Table 2.5: Pct Explained vs High Net Worth: Arrest, Victim, Pregnancy Outcome

Outcome	Arrest	Arrest	Incarceration	Incarceration	Pregnancy by 20	Pregnancy by 20
Net Worth	Low	Mid	Low	Mid	Low	Mid
Beliefs	30.2	19.59	22.83	17.04	10.56	13.03
Prob College	15.78***	9.51**	13.95*	7.26	8.13***	8.97***
Prob Work 20+ hrs	-0.39	0.46	-3.59	-0.28	1.19	0.64
Prob Arrest Next Year	7.75***	5.5**	6.55	6.42*	-0.36	-1.71
Prob Victim Next Year	1.57	-0.46	0.42	-1.68	-0.47	0.21
Prob Parent Next Year	5.49**	4.58**	5.5	5.31	2.08	4.92**
Total Difference	0.1211***	0.0904***	0.0587***	0.0431***	0.2028***	0.1159***
Total Explained	0.1020***	0.0873***	0.0473***	0.0358***	0.1686***	0.0936***

Hypothesis tests if explained portion equals zero, statistics are covariate explained portion divided by total explained
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

2.4 Discussion on Rational Expectations

2.5 Conclusion

Chapter 3

Seperating Beliefs from Reality in Higher Education

Is College Worth It For Me? Beliefs, Access to Funding, and Inequality in Higher Education

3.1 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 in families which adults have less 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 own 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. First, I focus on youth with high measures of academic ability and good behavior, which will be referred to as "High-Scorers," and I ask, how do differences in beliefs about own college ability affect inequality in bachelor's attainment rates for high-scorers. The measure of inequality that I use is the difference in bachelor's attainment rates between a given demographic group of interest and high-SES White youth. I focus on three demographic groups low-SES youth regardless of race, and Black and Hispanic youth, regardless of SES. In the process I also document how much of inequality is due to differences in financial assistance either from colleges, government, or family. This question is important to answer because if information frictions lead to underinvestment for high scorers from disadvantaged backgrounds than this could imply serious economic costs, such as foregone earnings or growth (Hsieh, Hurst, Jones, and Klenow 2020).

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. In contrast, differences in beliefs explains 15 percent of the Black high-scorer gap. However, I am unable reject a null hypothesis of a zero effect of beliefs on the Black high-scorer gap. Additionally, I find that for all three comparison groups differences in financial assistance play big statistically significant roles in explaining gaps, where explained contributions range between 45-50 percent depending on demographic group.

I then turn to studying policy interventions designed to narrow overall inequality regardless of ability. In particular, 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 better information to all? I use the same measure of inequality as in the decomposition exercise, but this time not restricting the analysis to high scorers. The efficiency measure that I use to evaluate the policies is college mismatch, which is the percentage of youth who would make different bachelor's attainment decisions should they have complete knowledge about ability. This takes the form of over-investment of low-scoring youth, and under-investment of high-scoring youth in education. The more 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.

I find that the targeted policy (providing information and funding only to low-SES high scorers), is the most efficient policy at reducing inequality, because it most effectively narrows bachelor's attainment gaps. The reductions range between 25-42% depending on demographic group[1]. The targeted policy also decreases mismatch by encouraging more education investment from high-scorers and thus overcoming underinvestment in higher education. Free college for all decreases inequality at the cost of increased mismatch, because bachelor's attainment rates increase primarily among low-scorers who would not complete college if they knew their scorer type with certainty. This happens because low scorers are too optimistic relative to the their actual ability. Although the tracking system reduces mismatch, it increases inequality, because increases in bachelor's attainment among high-scorers are offset by decreases in bachelor's attainment from low-scorers who comprise a larger fraction of the population for the groups of interest.

My analysis is based on a dynamic discrete choice model with credit constraints, heterogeneous financial support, and heterogeneous beliefs about ability. The model includes two latent ability types, low and high-scorers, as well as learning about 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 because 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 one's ability type. I estimate the proportion of high scorers outside of the model by using a finite mixture model with

[1] It reduces the Black gap by 25%, Hispanic gap by 28%, and the low-SES gap by 42%

two latent types governing earnings, grades, and human capital measures. I estimate the distribution of beliefs together with the remaining model parameters via indirect inference. The identification of beliefs comes from two important targets: the coefficient from self reported beliefs about college outcomes regressed on enrollment, and the coefficients from grade categories regressed on college exit, both holding financial assistance and demographics constant[2].

Estimating beliefs in this way allows beliefs to not be restricted to be rational priors that match the ability distributions estimated from the data. It also allows the distribution of beliefs to differ by demographic groups. The model and the estimated prior beliefs allow me to examine how within ability groups, beliefs differ with respect to actual latent type and hence generate mismatch. They allow me to examine how they differ with respect to rational priors and hence how providing information affects choices. They also allow me to examine how they differ by demographic group and hence affect inequality.

Overall my results 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,substantial inequality remains even after this intervention. This is because differences in early childhood human capital investment are important in explaining differences in bachelor's attainment rates by demographic group. This suggests that further understanding what generates higher education gaps requires not only uncovering what leads to differences in beliefs (DeLuca, Papageorge, Boselovic, Gershenson, Gray, Nerenberg, Sausedo, & Young 2021), or what affects differences in early childhood human capital stock (Cunha & Heckman 2007; Moschini 2021) but also how beliefs interact with human capital investment at the individual and parent's level (List, Pernaudet, & Suskin 2021).

3.1.1 Contribution to the Literature

This paper contributes to the structural modeling literature that focuses on the role of information frictions in higher education decisions. One strand of previous work uses nationally representative panel data to study the role of information frictions in the decision to go 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 include subjective beliefs and 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).

My paper is closest to Arcidiacono, Aucejo, Maurel, and Ransom 2016. As in this paper, I bridge the two strands of the literature by examining the role of information frictions on education outcomes while controlling for selection into college through enrollment. This paper's main innovation is to relax the rational expectations

[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.

[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.

assumption, that assumes agent's initial prior beliefs about own ability (in this case scorer type) are identical to the ability distribution observed in the data. I am able to separately estimate the initial prior distribution of beliefs by using data on self-reported beliefs about higher education outcomes and predicted model behavior. Specifically I do this by targeting the relationship between measured beliefs and college outcomes, as well as differences in non continuation by grade in the data that corresponds with the learning mechanism in the model.

Because of this there is room for beliefs to be too optimistic or too pessimistic relative to rational expectations. Additionally the distribution of beliefs can differ by demographic group, which allows differences in beliefs to play a role in generating inequality in higher education outcomes. Under rational expectations this heterogeneity would likely be captured by differences in the residual of the model. Therefore relaxing this assumption not only allows me to better estimate the role that beliefs play in generating outcomes, but also more accurately estimate efficiency commonly measured by ex post regret (referred to earlier as education mismatch) in the literature, as well as the effects of policy on outcomes and efficiency.

This paper also contributes to the empirical literature documenting that information campaigns can increase enrollment and completion for high achieving students from lower 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 could increase representation in higher education and decrease mismatch across the United States. These policies can be more effective and generate less inefficiencies than free college for all. They are also likely to be less resource intensive than subsidizing college for everyone.

3.2 Empirical Analysis and Facts

Before discussing the model, this section will show that in the data subjective beliefs are highly correlated with parental education and high school peers college plans as well as with outcomes like 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.

3.2.1 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.

In the analysis that follows I control for cognitive human capital through the Armed Services Vocational Aptitude Battery (ASVAB) Armed Forces Qualifications Test (AFQT), which scores a youth's performance on mathematics and verbal test scores. The units of measurement for AFQT are percentiles. I also control for non-cognitive human capital using indicators for adverse behavior at young ages including sex before age 15, ever committed an act of violence before the start of the survey, and ever stole a value greater than $50 before the start of the survey.

3.2.2 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 12 and Table 13. 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 the NLSY97, a good portion of the disparities in schooling outcomes and beliefs for Black and Hispanic youth can be explained by observables. Despite less enrollment, continuation, and optimism on average, in the analysis that follows, being Black or Hispanic is strongly positively correlated with enrollment and optimism towards enrollment. College completion and beliefs about having a degree by age 30 are also strongly positively correlated with being Black, holding all else constant[4]. For Black and Hispanic youth, a large portion of the unconditional gap in schooling and beliefs can be explained by parental education, house hold net worth and human capital measures, with some unexplained portion remaining significant for Hispanics regarding parental education effects on beliefs (see Oaxaca Blinder decompositions in Table 15-17 in Appendix section A.2 and summary statistics Tables 12-13 in Appendix A.1.).

Table 1 studies whether self-reported beliefs are positively correlated with schooling outcomes. The measure of beliefs is the College Outcomes Belief variable which is self reported probability of having a degree by age 30 for those born before 1982 and self reported probability of enrolling in college for those born after 1982. It shows that parental education and self reported beliefs about college outcomes are highly correlated with college enrollment, college continuation, and hence bachelor's degree attainment. Additionally, there is a strong role for parental education as well. Table 1 shows that holding all else constant if my parent's average years of schooling

[4]The positive coefficient on beliefs and on outcomes could be consistent with pessimistic initial beliefs, where beliefs that are measured are a weighted average from the prior and some signal. Then holding signal and prior constant, a positive coefficient for race/ethnicity means that the noise in the signal is positive, meaning grades where higher than expected. To test this on beliefs, early and later measures are needed. But if enrollment increases with higher measured beliefs than the positive coefficient for race/ethnicity is consistent with more pessimism that was adjusted upward more rapidly because of downward bias.

Table 3.1: College Outcomes

VARIABLES	(1) Ever Enrolled	(2) Bachelors Attained	(3) Complete College
Parent Education	0.0292***	0.0375***	0.0427***
	(0.0048)	(0.0056)	(0.0070)
Household 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)
College Outcome Belief	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 3.1: OLS Results: Higher Education Outcomes on College Belief

increases by one year, the probability I attain a bachelor's degree increases by 3.75 percentage points. Additionally if my self reported belief of having a degree by age 30 increases by 0.2, that probability of bachelor's attainment increases by nearly 4 percentage points. This increase in one year of parents education or 0.2 of my self reported beliefs, holding all else constant, is equivalent to a nearly $200,000 increase in household net worth, holding beliefs and parental education constant. The strong relationship between beliefs, parental education, and schooling outcomes continues to hold in Column 3 even with the inclusion of college GPA, and financial resources available in college. This is in addition to controlling for human capital measures, birth year, and geography variables.

Given the strong correlation between beliefs and schooling outcomes, Table 2 examines which covariates are strongly associated with beliefs. [5]. Table 2 shows that elements of a youths background like parental education and high school peer beliefs holding all else constant are associated with more optimism. An additional year in parents education is associated with a nearly 3 percentage point increase in the self reported probability of enrollment or degree by age 30. Number of peers with college plans is also positively associated with more optimism. If youth went to a high school where more than 90% of high school peers are planning on going to college as opposed to one where less than 10% were, than self reported probability of degree attainment and enrollment would increase by close to 20 percentage points. 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.

Although Table 1 establishes a relationship between beliefs and continuation, next in Figure 1 and Table 3, I evaluate the difference of college non-continuation behavior by observables, within grade categories. College non-continuation 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[6].

[5]Sample size differences in Table 2, is due to the fact that the probability of degree question was only asked to the older cohort, and probability of enrollment was asked for the younger cohorts while in high school. For Table 1 and the quantitative analysis a measure of beliefs combining both variables was used, see Appendix A.1.

[6]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.

Table 3.2: Measured Beliefs

VARIABLES	(1) Probability Degree	(2) Probability Enroll
Parent Education	0.0267***	0.0282***
	(0.0046)	(0.0058)
Household 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 3.2: OLS Results: Belief Regressed on Parent Education, Demographics, and Peers

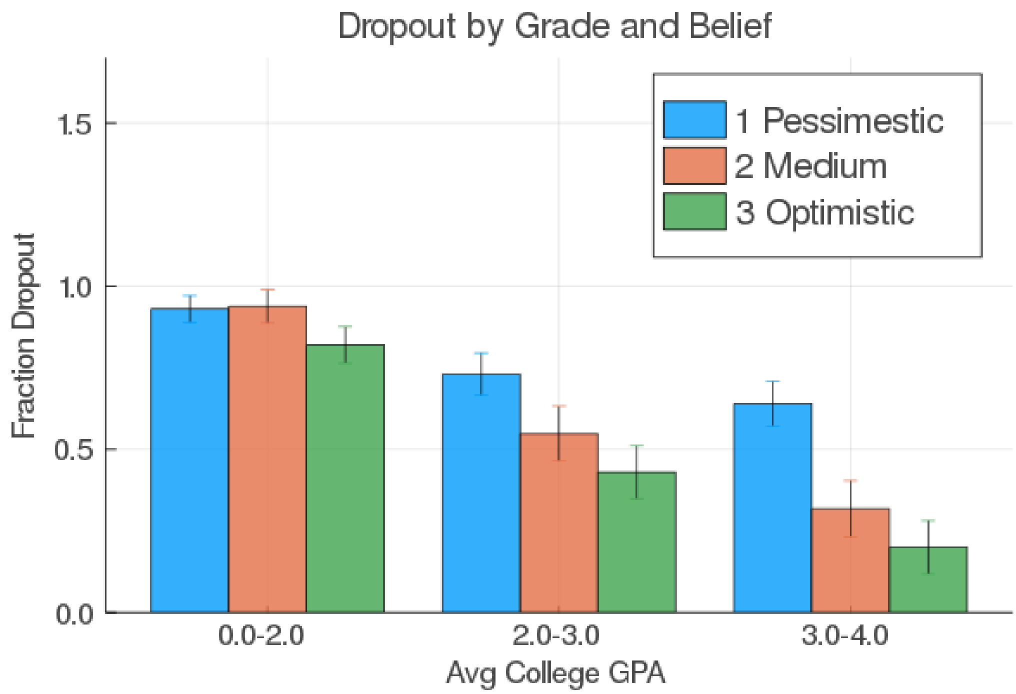

Figure 3.1: College non-continuation rates conditioned on grades/demographics.

Table 3.3: Non Continuation Interacted with GPA

VARIABLES	Non Interacted	Interaction GPA 2.0-3.0	Interaction GPA > 3.0
College Belief	0.0775	-0.2604**	-0.2249**
	(0.0543)	(0.1021)	(0.1092)
Hispanic	-0.0673		
	(0.0492)		
Black	-0.0539		
	(0.0413)		
Parent Education	-0.0179**		
	(0.0089)		
Household Net Worth ($1000s)	-0.00003		
	(0.00007)		
Total Govt/Inst Aid ($1000s)	-0.0179***		
	(0.0042)		
Total Fam Aid ($1000s)	-0.0118		
	(0.0072)		
Total Stud Loan ($1000s)	-0.0057		
	(0.0049)		
ASVAB AFQT	-0.001		
	(0.0007)		
GPA 2.0-3.0	-0.1513*		
	(0.0859)		
GPA > 3.0	-0.3431***		
	(0.0929)		
Geography Controls	Yes		
Birth Year	Yes		
Non Cognitive Controls	Yes		
Gender	Yes		
Observations	1,028		
R-squared	0.2576		

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

Table 3.3: OLS Results: College Non Continuation on Beliefs and Grades Interacted

Although non-continuation decreases with higher grades, Figure 1 shows that this exit behavior within grade categories differs by beliefs concerning bachelor's attainment. In Table 3 we control for measures of human capital and financial resources and still find statistically significant coefficients for the belief variable interacted with GPA category.

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, and high grades are a strong signal for high returns[7]. As suggested by the belief medium grade coefficient, more optimism might matter more for the medium grades, since the signal from medium grades is more ambiguous than low or high grades.

These results are consistent with predictions from Bayesian learnings models. In this case where beliefs about college outcomes reflect beliefs about ability and hence utility. Grades would therefore provide a signal of ability, where a better signal leads to more optimism and more continuation. As Table 3 shows, for any belief level, getting higher grades and hence a better signal leads to a higher probability of continuation. Since according to Bayes rule, beliefs are proportional to the prior times the probability distribution of grades, an ambiguous signal would make the posterior and hence continuation more dependent on the prior. Here we see that the marginal effect of beliefs is higher at medium grades which would be a more ambiguous signal then high or low grades. Additionally if agents are near certain of their type, then they would readjust their estimates less with bad signals, and hence exhibit more persistence. In fact as agents become more optimistic about college outcomes the difference in probability of continuation between high and medium grades decreases by 4 percentage points.

Altogether this analysis suggests a connection between subjective beliefs, parental education 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, which will be explored in the quantitative analysis of the paper.[8]

3.3 Economic Model

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

The economic environment consists of agents who live $T = 24$ periods, where each period lasts 2 years and represents an age span from 18-66. In each period agents can save or borrow up to a specified borrowing limit. Once an agent begins work, they do not return to school, so the education problem acts as a three stage problem. In the first stage agents decide to enroll or work until the end of the life cycle. If agent's enrolled in the first stage, then in the second stage agents choose to continue with school or work until the end of the life-cycle. Finally if agents chose to continue school, then in the third stage agents work for the remainder of the life cycle and

[7] Given by positive stand alone belief coefficient and the marginally significant stand alone coefficient for high grades

[8] 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.

realize type dependent earnings and non pecuniary utility.

In the model agent i has an unknown type $\tau_i \in \{\tau_h, \tau_l\}$ for being a high-scorer or low-scorer, respectively.The latent ability type τ_i determines the distribution of grades while in college $\pi(g_k, \tau_i)$ for $k \in \{l, m, h\}$, for low, medium and high grades respectively. The latent ability type τ_i also determines earnings $w_c(\tau_i)$, and non-pecuniary utility, $\mu_c(\tau_i)$ in the final stage of the model. The two variables for τ_i are hence a parsimonious one dimensional representation of the important role that cognitive and non cognitive skills play in generating education outcomes. Because of this τ_h represents the latent ability value of high-scorers since if an agent has τ_h they have a higher probability of achieving higher grades, higher earnings, and non pecuniary utility from college.

The realization of τ_i depends on true probability $P_{\text{true},i}$ of being type τ_h. This true probability depends on parental education, household net worth, race, ethnicity, sex, and measures of human capital. As such, it also captures the effect of early childhood human capital investment on educational attainment and earnings.

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. This subjective belief captures a broad belief about success at college for the individual, since an individual with $\tau_i = \tau_l$ is more likely to have lower grades, lower earnings, and less utility from graduating college.

3.3.1 Timeline of the problem

A decision tree representation of the problem is shown in Figure 2. In the decision tree subscripts are suppressed for ease of illustration. In the first stage 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 working and earning non college earnings w_n for the rest of the life cycle, or enrolling in college where they pay net tuition, $f_{1,i} = tuit_1 - Aid_{GC,i} - Aid_{Fam,i}$, which is the sticker price net of financial aid from government/colleges and families for the first period of life.

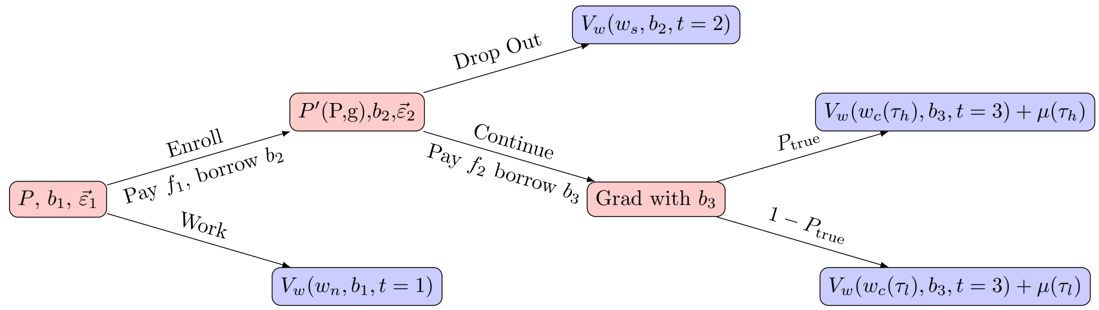

Figure 3.2: Decision tree representation of the quantitative model

In the second stage agents realize a signal for their latent type given by the GPA g_i during 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 period 2 net tuition $f_{2,i} = tuit_2 - Aid_{GC,i} - Aid_{Fam,i}$ for another period, or exit to work for the rest of their lives and earn w_s each period.

If agents complete school then after they work and earn earnings that depends on their type, $w_c(\tau_i)$ each year and receive non monetary utility $\mu(\tau_i)$ from work. Agents make borrowing and 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 $-B_s(t) \geq -B_n(w)$. Hence credit constraints are tighter while enrolled in school (Lochner and Monge-Naranjo 2012).

Heterogeneity by parental background, race, and ethnicity enters the problem through four channels. The first one is the distribution of initial subjective beliefs P_i of one's own ability type.The second is through transfers from parents, as well as from the government, and colleges that often provide need based financial assistance. This second channel leads to differences in net tuition $f_{t,i}$ for $t = 1, 2$ while in school. The third channel is the true probability of being type τ_h, $P_{\text{true},i}$ which determines the distribution of grade realizations and future earnings. Finally, the fourth channel is the distribution of non-pecuniary utility shocks $\vec{\varepsilon}_{t,i}$.

The model has no explicit role for discrimination. However discrimination could enter the problem through past policies that created differences in parental education and net worth. It can enter through the amount of aid the government or colleges distribute. It can enter through wages and grades, and hence $P_{true,i}$. It can also enter through early childhood human capital that determines the realization of human capital measures.

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 returns to years of schooling regardless of one's 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 are unable to consumption smooth and face lower consumption for the first two periods of their life. If youth receive less financial assistance during college, or are more pessimistic about being a high scorer, than this will make college less appealing for students from demographic groups where this is more likely the case.

3.3.2 Enrollment Stage

At age 18, agents either enroll in school or work. If they choose to work at this stage they will do so until the end of the life cycle. Agents begin with a belief P_i that they are of type τ_h, a net tuition realization $f_{1,i}$, initial assets $b_{1,i}$, and unobserved tastes for college and work $\vec{\varepsilon}_{1,i} = (\varepsilon_{c,1,i}, \varepsilon_{w,1,i})$. The agent's stage 1 problem is thus given by (3) below, where $V_w(w_n, b_{1,i}, 1) + \varepsilon_{w,1,i}$ is the utility from working and $V_{c,1}(P_i, f_{1,i}, b_{1,i}) + \varepsilon_{c,1,i}$ is the utility from enrolling in college.

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

$$s.t.$$

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

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 $\pi(g_k, \tau_j) = Prob(g_k | \tau = \tau_j)$.

$$(4) \quad P'(g_k, P_i) = \frac{P_i \times \pi(g_k, \tau_h)}{P_i \times \pi(g_k, \tau_h) + (1 - P_i) \times \pi(g_k, \tau_l)}$$

3.3.3 Continuation Stage

At age 20, agents make the decision to continue and complete college or exit and work for the remainder of the life cycle. Agents observe GPA g from the first stage and then update belief P_i to $P'(g, P_i) = P'_i$. They realize period 2 net tuition $f_{2,i}$ and begin the second stage with debt/savings from the first stage $b_{2,i}$. They also 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

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

$$s.t.$$

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

During college grades reveal information about τ_i because the grade distribution depends on τ_i. But because τ_i also determines one's non-pecuniary utility, the information revealed in school can also include psychosocial elements of higher education that are often discussed in other contexts[9]. In this model, the assumption is that this is closely tied to grade performance, and a bad signal in grade 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 are captured by a age-constant location parameter of non-pecuniary shocks $\vec{\varepsilon}_{t,i}$.

3.3.4 Workers Problem

Finally, the workers problem is given by (1) below. The state variables are earnings w, assets/debt b_i, and age t.

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

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

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

For every period the borrowing constraint is given below. Therefore in the final period $b_{T+1} = 0$.

$$\tilde{B}_{T-n}(w) = \sum_{m=1}^{n} w(1+r)^{-m} \quad \text{for} n \geq 1$$
$$\tilde{B}_T = 0$$

3.3.5 Optimal Choice

Since in the first two stages the agent faces a discrete choice problem, the optimal decision for each agent is described by a cutoff rule with respect to one's belief about one's type. If P_i is higher than a certain threshold the agent will enroll. For example in the first stage the optimal decision is characterized by equation 6 below, where $\sigma_{d,2}, \mu_{d,2,i}$ are the normalized scale parameter and location parameters[10] for the Type I extreme value shocks.

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

[9]Examples include differences in the prevalence of impostor syndrome or stereotype threat by race, gender, ethnicity discussed in the sociology literature.

[10]Normalized with respect to the difference in Type I extreme values. This because the difference in shocks is what is identified

.

Similarly, in stage 2, given $\{\pi(g_k, \tau_j)\}_{k,j}$ 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.

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

.

The cutoff rules holding non-pecuniary utility shocks and distribution constant, allow us to predict the effects of financial assistance, subjective beliefs, and human capital embedded in $P_{true,i}$.For instance, if the distribution of non-pecuniary utility is such that utility from the decision to work is less than the utility from college for being τ_h, and greater than the utility from college for being τ_l, then the decision rules are strictly increasing in $f_{1,i}, f_{2,i}$, depending on the period. $P'(g_i, P_i)$ also increases in P_i and for $P_i \in (0,1)$, if higher grades provide a strong signal of being τ_h, $P'(g_i, P_i)$ will increase in g_i. Therefore probability of enrollment and probability of continuation would increase with financial assistance, one's belief about being τ_h, and with higher $P_{true,i}$.

3.3.6 Example for Model Prediction

We now turn to illustrating how financial assistance, subjective beliefs of being τ_h, and grades (whose realizations reflect earlier human capital investments) affect one's 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, the probability of enrollment displays a flat portion and then increases with subjective beliefs. This is the case for all net tuition levels displayed in the graph. Thus if two youth have the same beliefs but different access to resources, their probability of enrollment will still be different. Likewise, if their access to resources is the same but beliefs differ, their probability of enrollment also differs.

Figure 4 shows that conditional on enrolling, probability of continuation differs by grade revelation. This illustrates how learning affects one's continuation decision. After a certain belief threshold, higher grades thus lead to an increase in one's probability of continuation. The large difference in continuation probability between high grades and medium grades diminishes as a youth become more optimistic.

Figure 5 takes probability of obtaining a degree and shows that even though the effect of net tuition is somewhat more muted than in Figure 3, net tuition and subjective beliefs about being a high-scorer still affect one's probability of obtaining a degree.

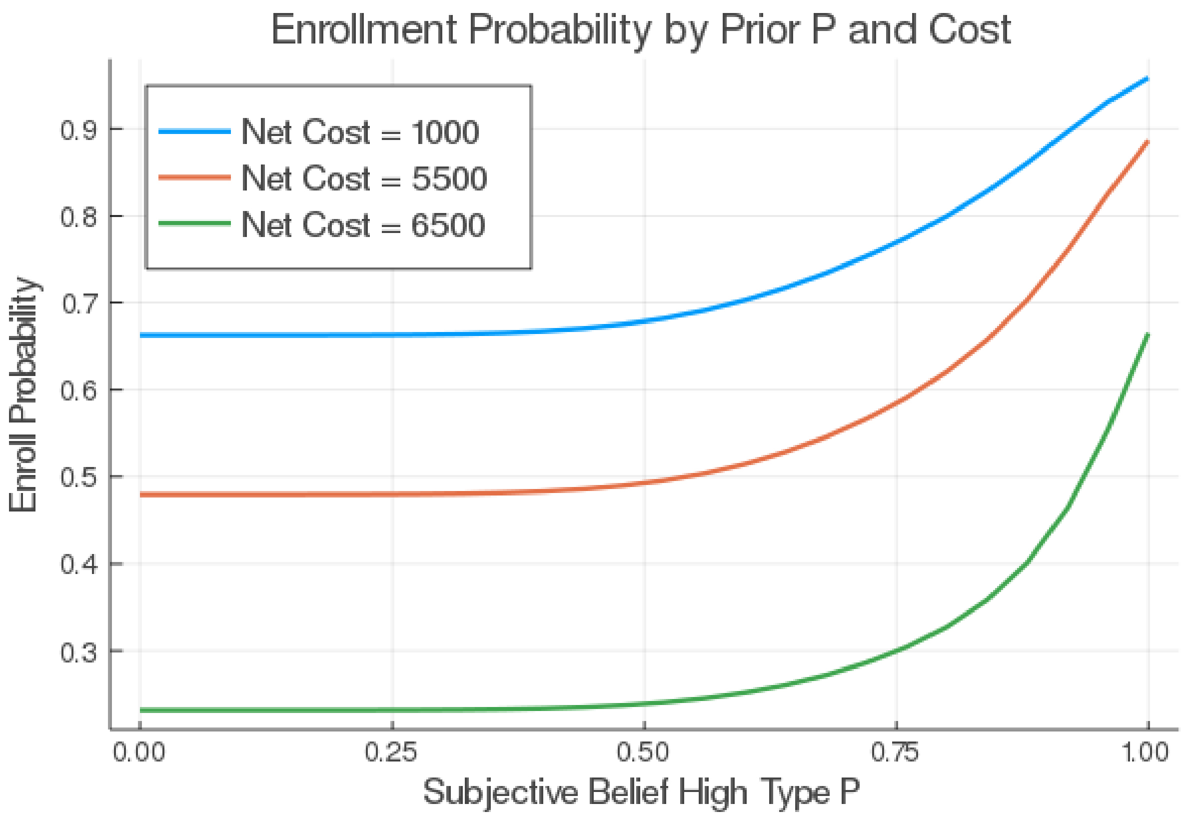

Figure 3.3: Model predicted probability of college enrollment by net tuition and prior subjective belief of being a high-scorer.

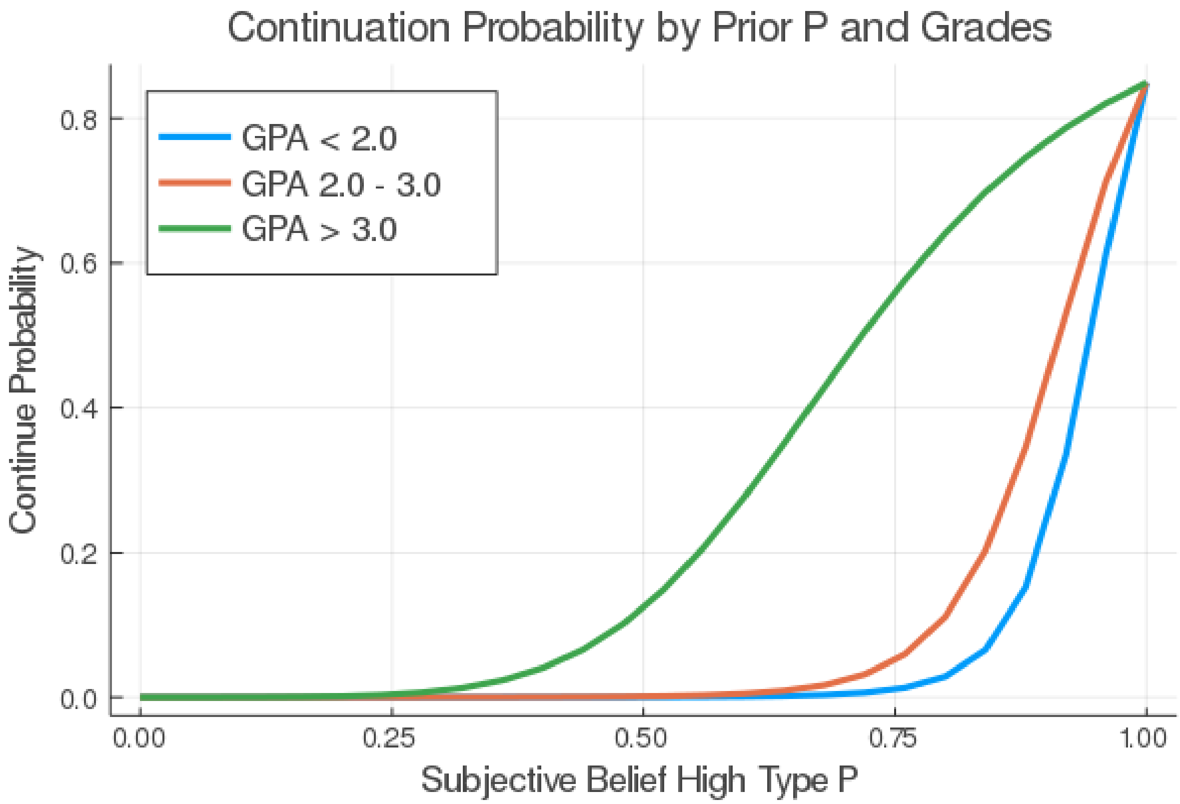

Figure 3.4: Model predicted probability of college continuation by average GPA realized before the second stage after the first stage.

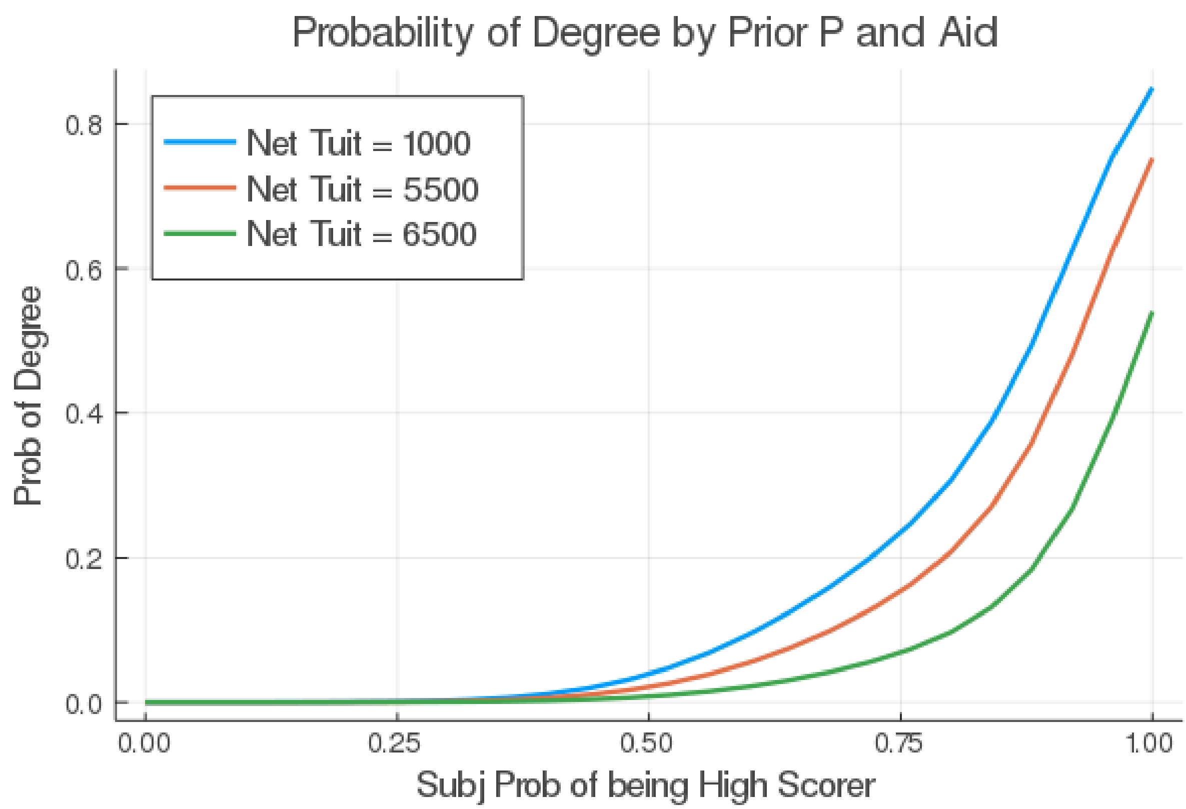

Figure 3.5: Model predicted probability of bachelor's attainment by net tuition.

3.4 Estimation of Quantitative Model

In this section I discuss how I identify and estimate the parameters of the structural model described in section 3. Specifically, I describe some of the assumptions governing the distribution of earnings, financial assistance, and probability of being a high type, as well as parameters whose values will be set outside of the estimation routine. I discuss what moments are used to identify parameters related to the distribution of beliefs about one's type.

Table 3.4: 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 3.4: Table of Preset Parameters.

3.4.1 External Parameters

The parameters I 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, \$46,000, which likely reflects the use of private loans amongst some students (Lochner and Monge Naranjo 2010).

Financial assistance is estimated outside of the model. The distribution of financial assistance is assumed to follow a log normal distribution, of the form below, where parameters are estimated by OLS.

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

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/college 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 determined through the estimation of the three following measurement equations in the finite mixture model.

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

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

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

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 the specification for $Z_{i,j}$ follows Hai and Heckman 2017.

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

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 degree $s \geq 16$.

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.

The distribution of type will also be important for the effect of policies targeting by ability as 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 finite mixture model can be estimated using the individual likelihood function given by $f(\vec{Z}_i, w_i, g_i; \tau_k, X_i, s)$. These parameters in (9)-(12) are estimated by solving for the maximum likelihood given below in equation (13). 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.3-A.4.

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

After estimating financial assistance and the finite mixture model, I use the sum of the predicted financial assistance variables for total financial assistance, and predicted earnings from $\ln w_{i,s}$ for $w_n, w_s, w_c(\tau_l), w_c(\tau_h)$[11]. I use the finite mixture model $\pi(g, \tau)$ for the conditional grade probabilities that are used as signals and determine grade realizations. The individual probability of being a high-scorer that I use, $P_{\text{true},i}$, is explained below in equation (14).

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

$P_{\text{true},i}$ is therefore the posterior probability of being a high-scorer, given education outcomes, earnings, grades, and human capital measures estimated from the finite mixture model. $P_{\text{true},i}$ will be used to simulate high types and low types in the quantitative model. Given the simulated type the appropriate $\pi(g, \tau)$ will be used to generate grades for those missing grades.

3.4.2 Internally Estimated Moments

The remaining parameters that are estimated are the sticker price of tuition for stage 1 and stage 2, $tuit_1$, $tuit_2$, the distribution of subjective beliefs of being type τ_h, the non-pecuniary utility that depends on type, $\mu_c(\tau_i)$, as well the distribution of non-pecuniary utility shocks. The distribution of non-pecuniary utility shocks is given by the type I extreme value draws whose location parameters differ for White, Black, and potential first generation students. The scale parameter for the type 1 extreme value shocks are allowed to differ by stage.

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

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

The assumption used in equation (14) is that data contained in the variable $CollBelief$ which is equivalent to College Outcome Belief in Table 1 and 3 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 one's and zero's

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

since these imply certainty of type. Thus these beliefs are not amenable to change 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 boot strapping. The moments that will 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.

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. The vector $\tilde{\beta}(\Gamma)$ is the vector of simulation coefficients given Γ, while the vector $\vec{\beta}$ is the vector of regression coefficients from the data. The weighting matrix is given by W which is the inverse of the diagonal matrix of the standard errors from the data regression coefficients.

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

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 will 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.

3.4.3 Identification Discussion

This section briefly discusses the identification strategy used to choose the targeted moments to estimate the parameters. For a quick reference see Table 5.

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.

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. The importance of beliefs also depend on 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 utility from college between low and high types is also determined by $\mu_c(\tau)$. The difference in expected utility between school and work is also determined by the location difference of type I extreme value shocks for school and work.

If the difference in utility between school and work,[12] is such that work is always preferred, or college is always preferred, then we would have trouble matching some of the patterns between beliefs, grades, and outcomes observed in the data. If type dependent non pecuniary utility $\mu_c(\tau)$, is such that there is no difference in utility between high and low scorers than we would have the same problems matching patterns in the data. This restricts these parameters to be such that there is an effect of measured beliefs and grades.

[12]College minus work type I extreme value shocks

Table 3.5: Identification Strategy

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: Parent Education HSD	$\beta_{C,PH}$	Coefficient $Pedu_{hsg}$ on continuation
$\gamma_{p,s}$	Belief: Parent Education SCOL	$\beta_{C,PS}$	Coefficient $Pedu_{scol}$ on continuation
$\gamma_{p,c}$	Belief: Parent Education Bach	$\beta_{C,PB}$	Coefficient $Pedu_{bach}$ on continuation
$\mu_{d,0}$	Non-Pec Util: Black 1st Gen Col Stud	$\beta_{E,0} + \beta_{E,1G}$	Constant and $FirstGen$ Coefficient on enrollment
$\mu_{d,C}$	Non-Pec Util: Col Educated 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 3.5: Identification of Model Parameters and Targeted Moments.

Given these restrictions on 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}, as well as the constant term in continuation $\beta_{C,0}$. We can also see in Panel 1 of Figure 6 that high and low grades do provide strong signals of type. For medium grades this is less so.

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.

Panel 2 in Figure 6 shows the updated belief given the type-dependent grade probabilities in Panel 1. Figure 6 shows that grades do provide a signal of type showing that there should be a differential response in non-continuation of grades.

The level of beliefs given through $\gamma_{p,0}$ is identified through difference in response to GPA. Therefore the degree to which grades affect updating and hence continuation depends on the location of the distribution of the prior. If estimated

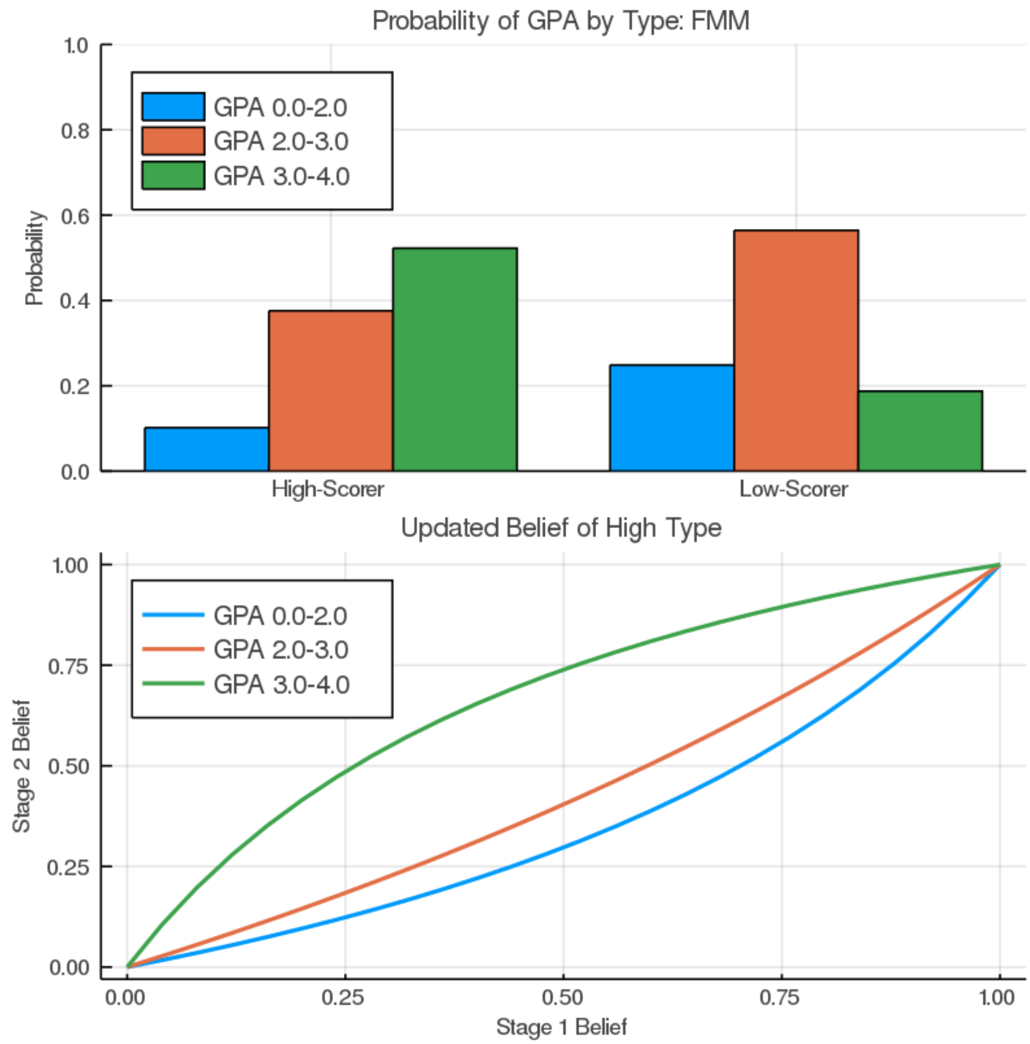

Figure 3.6: Grades by latent scorer type, and update rule by initial prior.

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 as suggested by Figure 6 Panel 2. 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 (15) and (16), given by $\beta_{C,W}, \beta_{C,H}, \beta E, W, \beta E, H$. 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 $\pi(g_k, \tau_j)$ is too restrictive. In total there are 16 parameters that are estimated by 17 moments.

Table 3.6: 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 3.6: Mean Estimated Earnings from Finite Mixture Model.

3.4.4 External and Internal Estimation results

This section discusses some of the main results from the internal and external estimation of the quantitative model. For the full results of the financial assistance estimates, the finite mixture model, and the indirect inference specification see appendix A.4 and A.5.

Table 6 shows the estimated 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 3.7: 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 3.7: Internally Estimated Parameters with Bootstrapped Standard Errors.

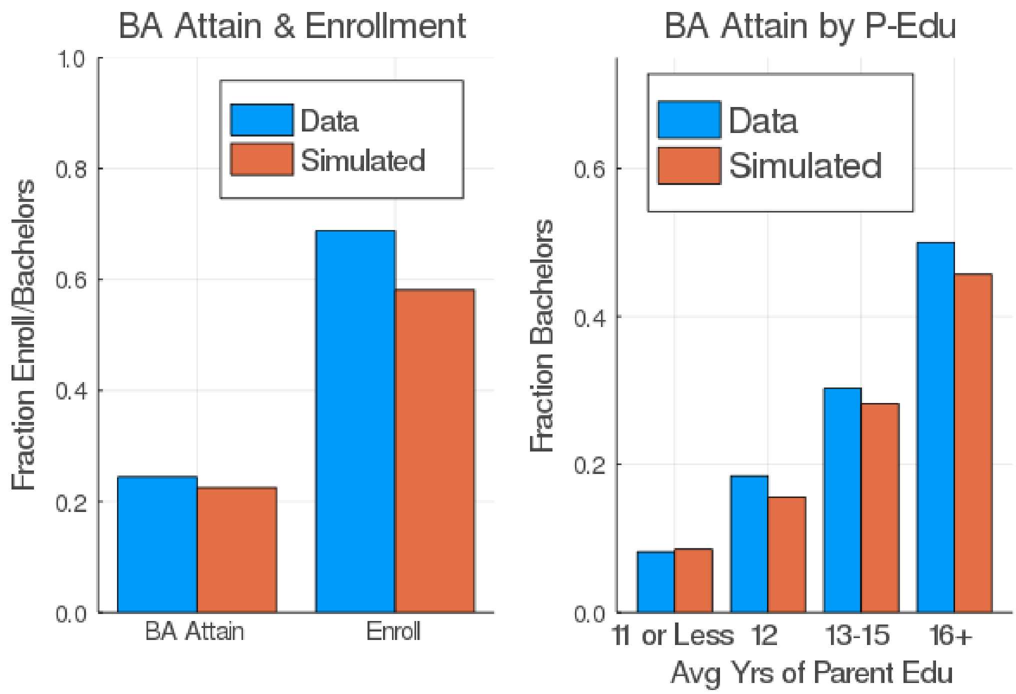

Figure 3.7: Model Fit: Enrollment, Bachelor's Attainment by Parent Edu.

Table 7 shows several of the key parameters that were estimated in the internal calibration exercise. The coefficient on self-reported 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 college ability higher and perhaps closer to the truth if they are high-scorers.

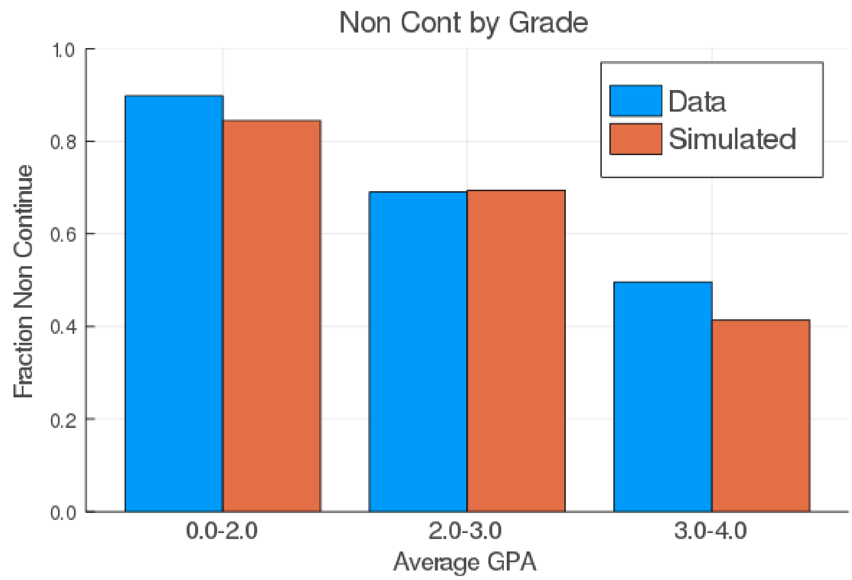

Figure 3.8: Model Fit: Non Continuation by Grade

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.

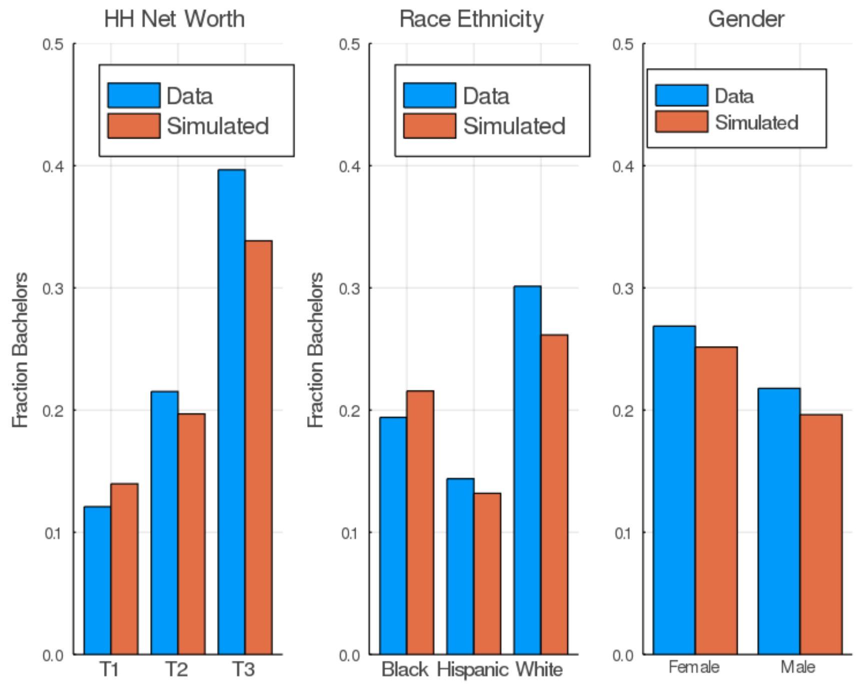

Figure 3.9: Model Fit: Bachelor's Attainment by Demographics

3.5 Quantitative Results

In this section I 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 addresses these disparities by targeting information and funding to high scorers from low-SES backgrounds be more efficient at closing overall bachelor's attainment gaps[13] than universal policies such as free college for all or providing better information to everyone in the United States.

For both questions the main outcome of interest, bachelor's attainment gaps, is defined as the difference in bachelor's attainment rates between high-SES White youth versus the three comparison groups, Black, Hispanic, and low-SES youth[14]. 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

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

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

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 discuss the estimated information frictions and mismatch present in the baseline version of the model.

3.5.1 Information Frictions and Mismatch

In this section I discuss information frictions and mismatch by scorer type, with some discussion on how this differs by demographic group. I 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.

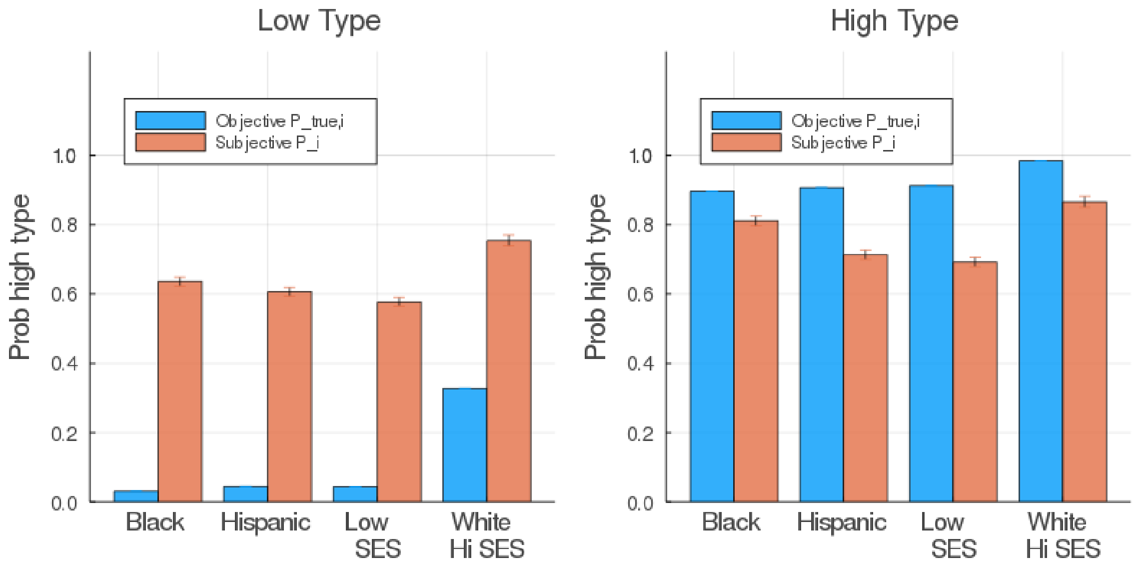

Figure 3.10: Information Friction: Objective vs Subjective Probability of High Type

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.

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 the universal information policy and the targeted policy, will have different effects by type. For instance universal information should lead to a bigger readjustment of low-scorers' beliefs than for high-scorers' beliefs. As a result this can 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 to low-SES youth more than for Hispanic and Black youth. This is because Black and Hispanic youth benefit only to the extent that they are also low-SES high scorers. Most importantly, the difference in beliefs with respect to $P_{\text{true},i}$ is larger for low-SES youth than for Black and Hispanic high-scorers.

Figure 10 can also help us predict the effect of 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.

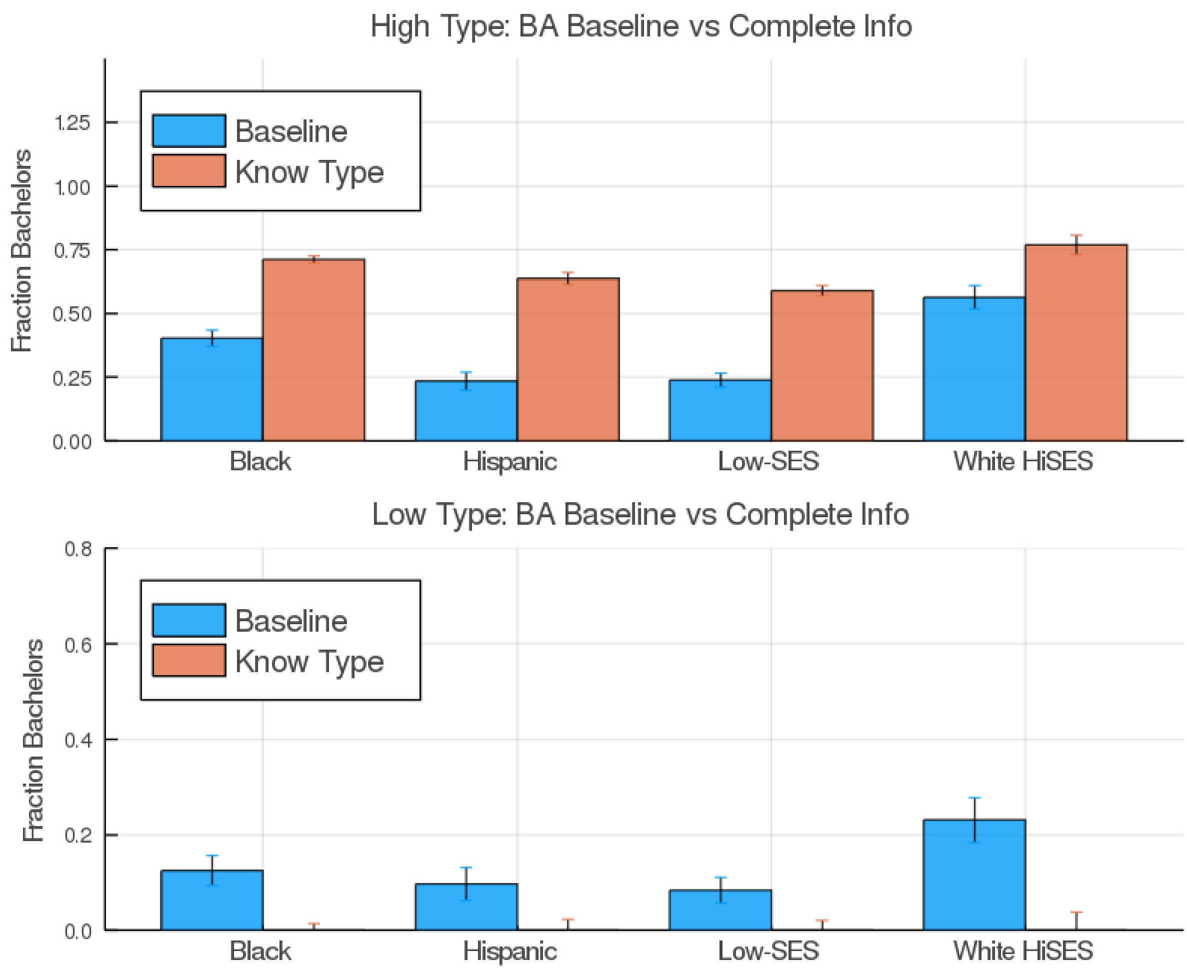

Figure 3.11: Inefficiency from Info Friction: Mismatch by Type Under Complete Info

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.

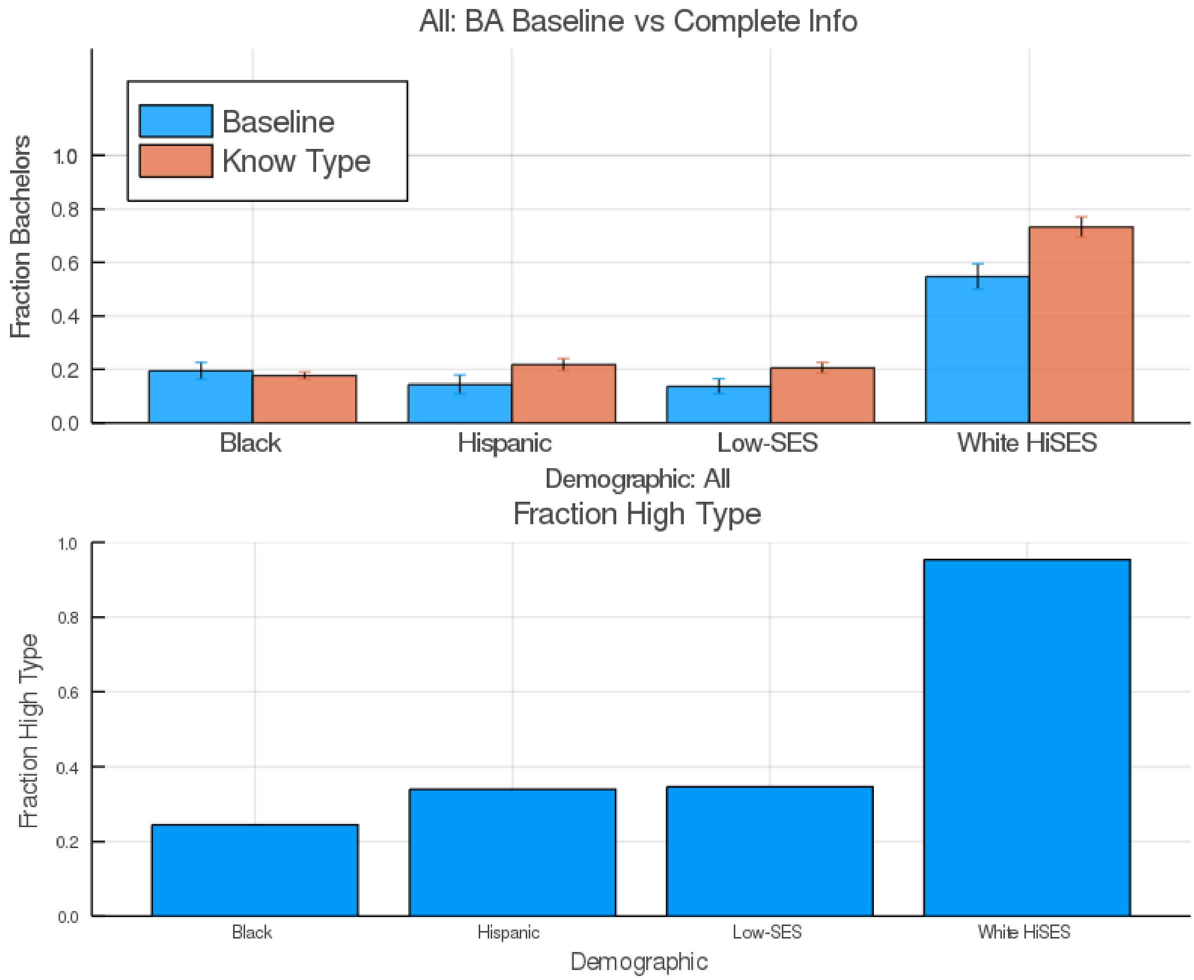

Figure 3.12: Aggregate Mismatch by Type and Proportion of High Type by Group.

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.

Relaxing the rational assumptions prior common in the literature allows for a more accurate estimation of mismatch as well as the results of providing information. What Figure 11 and 12 show is that if rational expectations were assumed then the residual dependent on race or dependent on race and ability would have to adjust so that bachelor's attainment matches the baseline. In this case the effect of information would be muted and estimates of mismatch would lower since differences in non pecuniary utility would play a bigger role in explaining inequality.

In summary the difference of beliefs with respect to $P_{\text{true},i}$ and with respect to the actual individual's 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.

3.5.2 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 assistance?

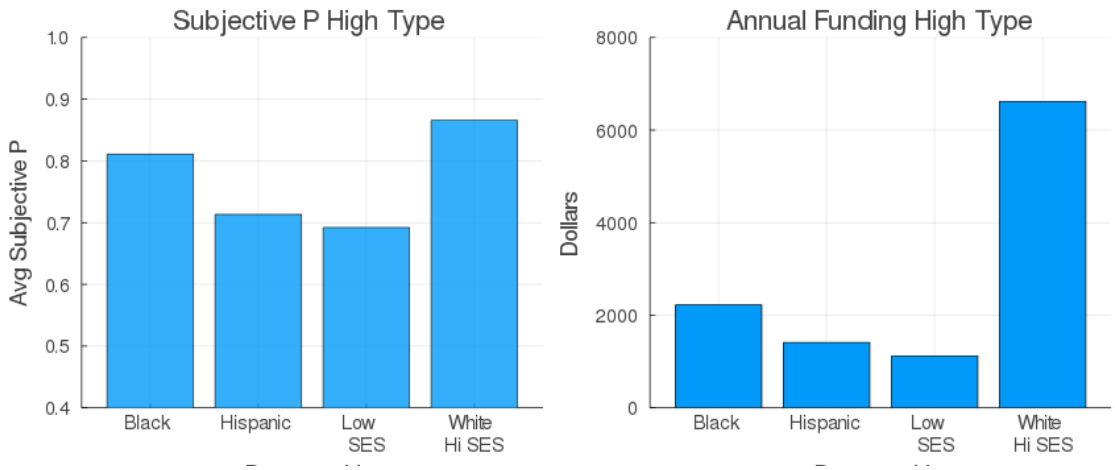

Figure 3.13: Group Difference in Causal Variables: Beliefs and Funding

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.

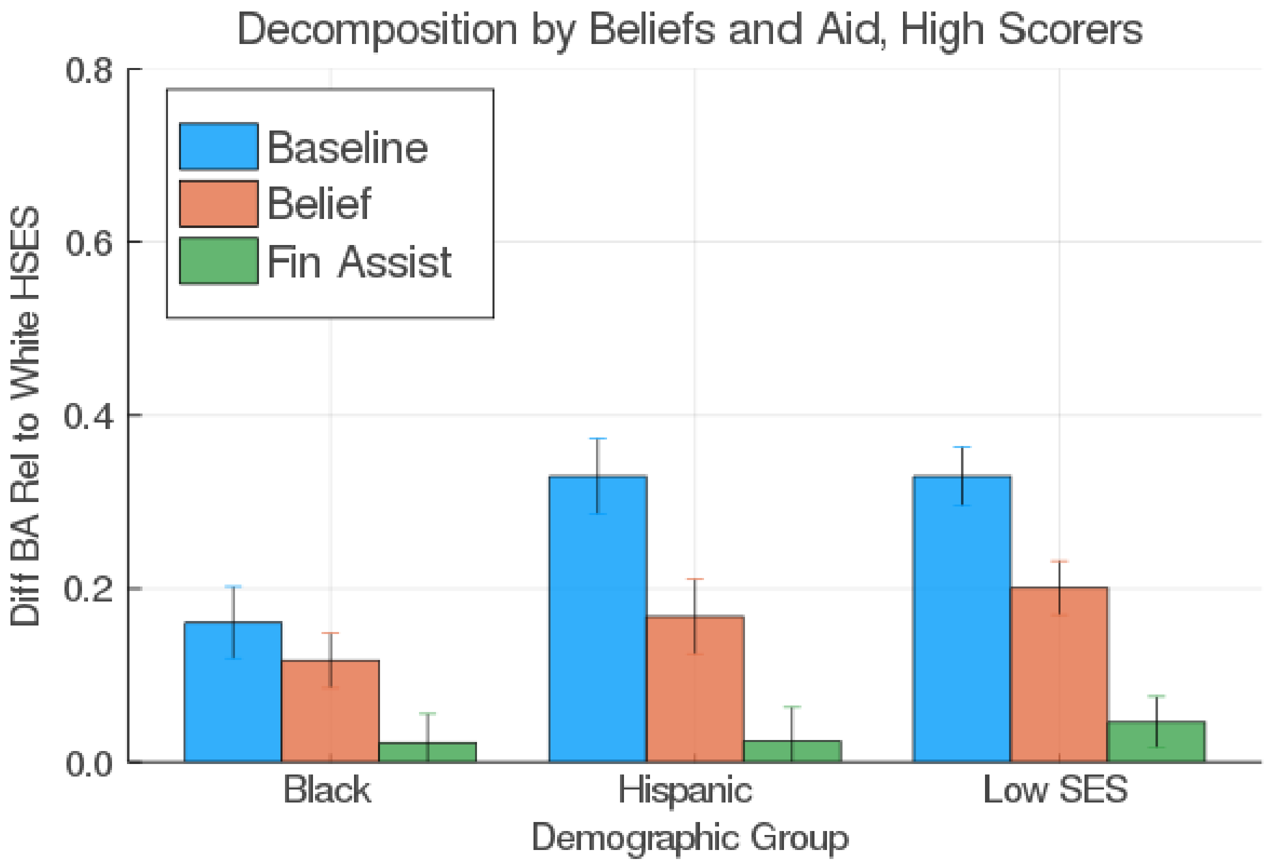

Figure 3.14: Decomposition of Bachelor's Attainment Relative ot White High SES

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.

Table 3.8: 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 3.8: Decomposition Results of Inequality in Bachelor's Attainment Relative to White High SES

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 of beliefs 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. Financial assistance explains 50% of the Black bachelor's attainment gap, and 45% of the bachelor's attainment gap for Hispanic and low-SES high ability youth. Since ability type is assumed to be equal any remaining difference is due to differences in non pecuniary utility.

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.

3.5.3 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 [15] 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 providing information about ability type to all. In the targeted and universal policies 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 $P_{true,i}$ that incorporates information that would be available before college completion. In effect providing information is equivalent to giving everyone rational expectations.

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

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

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%. Providing 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, where low scorers make up a greater share of the population.

Table 3.9: Policy Effect on Overall Inequality

Demographic	Baseline	Free College for All	Info to All	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 3.9: Policy Effect on Gap between White High SES and Comparison Group

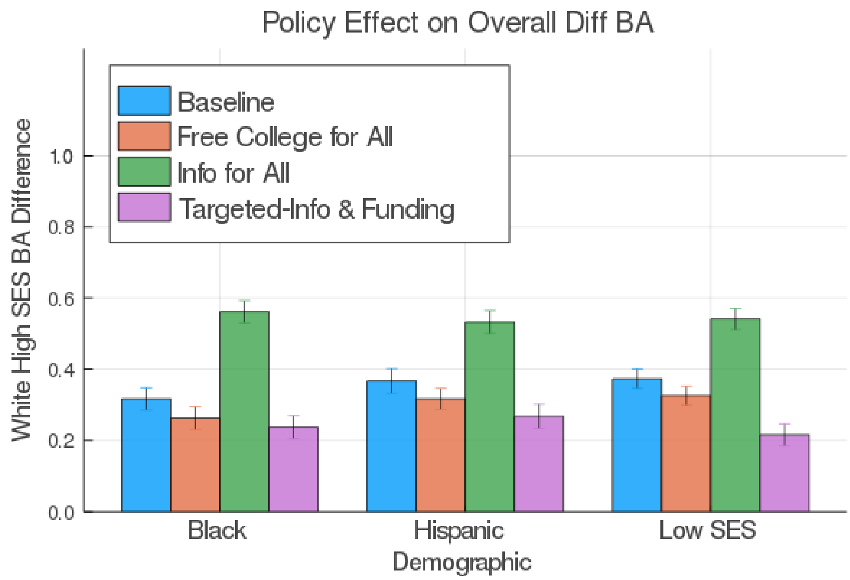

Figure 3.15: Policy Effect on Gap between White High SES and Comparison Group

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.

Table 3.10: 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 %
Info for All	4.4 %	4.1 %	0.3 %
Targeted: Recruiting	19.1%	13.3 %	5.9%

Table 3.10: Percentage of Population Mismatched by Policy

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 still plays in generating inequality. Specifically, even if the targeted policy lead to a 100% bachelor's attainment rate 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 through increases in education investments among 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. Providing information increases overall inequality which would make it undesirable if decreasing overall 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.

3.6 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 and access to resources, individual beliefs about own college outcomes are highly correlated with parental education, 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 overall 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 in addition to financial constraints, information frictions lead to high scoring youth from underrepresented backgrounds under investing in education. Because of that representation in higher education can be increased efficiently through more active recruiting along with subsidies for academic high achievers from disadvantaged backgrounds. However because of differences in early childhood human capital development 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, as well as the relationship between human capital investments, belief formation, and information frictions.

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Appendix A

Appendix to Chapters 1 and 2

A.1 Data Construction

A.2 Supplementary Figures Chapter 1

A.2.1 Oaxaca Blinder Output: Beliefs

Table A.1: Oaxaca Blinder: Belief Enroll College

Comparison Group VARIABLES	Low Net Worth overall	Low Net Worth explained	Low Net Worth unexplained	Mid Net Worth overall	Mid Net Worth explained	Mid Net Worth unexplained
Avg Years of Parents Schooling		5.3400***	5.8772		3.2661***	6.0701
		(0.8968)	(8.9540)		(0.5360)	(8.9576)
HH Net Worth ($10,000s)		0.7772	0.0047		0.3636	-0.3678
		(1.1997)	(0.6301)		(0.9082)	(2.5852)
Parent Ever in Jail		0.5193**	0.0573		0.0288	-0.0953
		(0.2367)	(0.2266)		(0.1057)	(0.2198)
Parent Serve in Military		0.0295	0.0795		-0.0037	0.6406
		(0.1020)	(0.6741)		(0.0227)	(0.6898)
Mom's Age at First Birth		0.4708	-6.6317		0.9160**	-16.4253***
		(0.5573)	(6.2373)		(0.3915)	(6.1787)
% Peers Coll Plan ($\sim$ 25 ppts)		2.3055***	-9.6571**		1.1388***	-6.0071
		(0.3734)	(4.6335)		(0.2526)	(4.9262)
% Peers Cut Class ($\sim$ 25 ppts)		0.2024	-0.4450		0.1420	-0.2409
		(0.2395)	(2.4149)		(0.1435)	(2.4870)
% Peers Sports/Clubs ($\sim$ 25 ppts)		0.0663	10.6139**		0.1809*	4.8678
		(0.1182)	(4.5549)		(0.0963)	(4.6953)
% Peers in Gang ($\sim$ 25 ppts)		-0.0512	-3.7144		0.0859	-3.2115
		(0.4316)	(2.5741)		(0.2530)	(2.6936)
ASVAB AFQT (10 percentile pts)		8.7380***	-5.2775*		4.9289***	-3.0551
		(0.8783)	(2.7254)		(0.5591)	(2.8666)
Ever Stole $50+ by age 18		0.1336	-0.4792		0.1575	0.2278
		(0.0951)	(0.4721)		(0.1014)	(0.4807)
Ever Attack Someone by age 18		0.4358*	0.9365		0.5152**	1.5693**
		(0.2633)	(0.6619)		(0.2013)	(0.6524)
Ever had Sex by age 15		1.2613***	-0.1753		0.8664***	0.0421
		(0.3736)	(0.7812)		(0.2593)	(0.7347)
Female		-0.3721***	0.8530		0.0666	0.7724
		(0.1398)	(1.1920)		(0.1258)	(1.0980)
Hispanic		-2.7732***	-0.6269		-0.9603***	0.1477
		(0.4211)	(0.4986)		(0.2369)	(0.4211)
Black		-3.5527***	-1.1882**		-1.9167***	-0.5862
		(0.5920)	(0.5630)		(0.3757)	(0.4736)
Lived Rural Area 1997		0.0792	0.5303		-0.0024	1.2225
		(0.3959)	(1.6829)		(0.0418)	(2.0782)
Lived Urban Area 1997		-0.4888	1.5248		-0.0676	3.4358
		(0.3583)	(4.4446)		(0.0947)	(4.6525)
Lived NE US 1997		0.0063	-0.4557		-0.0118	-0.0604
		(0.0193)	(0.5554)		(0.0381)	(0.5556)
Lived Western US 1997		-0.0116	-1.7449**		-0.1895*	-0.8027
		(0.0328)	(0.8069)		(0.1060)	(0.7195)
Lived Southern US 1997		-0.3431	-1.5941		-0.1213	-0.5701
		(0.2485)	(1.0758)		(0.1804)	(0.9877)
Year of Birth		0.0374	4,213.2215*		-0.0005	2,837.2919
		(0.0574)	(2,309.9813)		(0.0065)	(2,422.1206)
High Net Worth Avg	82.6298***			82.6298***		
	(0.8319)			(0.8342)		
Comparison Avg	63.3565***			71.2966***		
	(0.9090)			(0.9197)		
difference	19.2733***			11.3331***		
	(1.2322)			(1.2416)		
explained	13.4517***			9.5347***		
	(1.5957)			(1.1820)		
unexplained	5.8216***			1.7985		
	(1.8842)			(1.5016)		
Constant			-4,192.6749*			-2,821.0946
			(2,308.9083)			(2,420.9641)
Observations	2,760	2,760	2,760	2,501	2,501	2,501
N Comparison	1658	1658	1658	1399	1399	1399
N High Net Worth	1102	1102	1102	1102	1102	1102

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

Table A.2: Oaxaca Blinder: Belief Work 20+ hrs

Comparison Group VARIABLES	Low Net Worth overall	Low Net Worth explained	Low Net Worth unexplained	Mid Net Worth overall	Mid Net Worth explained	Mid Net Worth unexplained
Avg Years of Parents Schooling		0.4205	-1.7649		0.4169	-4.0515
		(0.4380)	(4.0972)		(0.2555)	(4.0494)
HH Net Worth ($10,000s)		-1.2055*	0.2811		-0.6282	-1.8720
		(0.6812)	(0.2643)		(0.5348)	(1.2300)
Parent Ever in Jail		0.0612	0.0296		-0.0303	-0.0053
		(0.1312)	(0.1321)		(0.0450)	(0.1183)
Parent Serve in Military		0.0765*	0.1469		0.0018	0.6073**
		(0.0432)	(0.2999)		(0.0067)	(0.3013)
Mom's Age at First Birth		0.4294	0.3531		0.1882	2.8196
		(0.3047)	(3.7689)		(0.2280)	(3.8156)
% Peers Coll Plans ($\sim$ 25 ppts)		0.2894	-1.2262		0.2997***	-4.0606*
		(0.1768)	(2.3295)		(0.1152)	(2.4633)
% Peers Cut Class ($\sim$ 25 ppts)		-0.0135	-0.0086		-0.0670	-0.9920
		(0.1116)	(1.1196)		(0.0601)	(1.0833)
% Peers in Sports/Clubs ($\sim$ 25 ppts)		-0.0735	1.8616		0.0683	-3.5322*
		(0.0629)	(2.1379)		(0.0433)	(2.1364)
% Peers in Gang ($\sim$ 25 ppts)		0.3790	-0.4248		0.1183	-0.8030
		(0.2306)	(1.2768)		(0.1212)	(1.2778)
ASVAB AFQT (10 percentile pts)		2.9448***	-6.5698***		0.6515***	-1.4536
		(0.4544)	(1.3541)		(0.2505)	(1.3617)
Ever Stole $50+ by age 18		0.0470	-0.0291		0.0178	-0.1292
		(0.0509)	(0.2412)		(0.0249)	(0.2127)
Ever Attack/harm Someone by age 18		-0.1044	0.0025		-0.0915	-0.0459
		(0.1386)	(0.3096)		(0.0923)	(0.3000)
Ever had Sex by age 15		-0.3951**	-0.3054		-0.0884	0.1438
		(0.1953)	(0.3750)		(0.1197)	(0.3427)
Female		-0.0134	0.0723		-0.0005	0.2665
		(0.0353)	(0.5776)		(0.0051)	(0.5482)
Hispanic		0.0113	-0.0379		0.0084	-0.0553
		(0.1960)	(0.2469)		(0.1080)	(0.2101)
Black		0.1791	-0.0778		0.2275	0.1589
		(0.2999)	(0.2822)		(0.1702)	(0.2239)
Lived Rural Area 1997		-0.1332	-0.0876		-0.0124	0.1730
		(0.1355)	(0.5653)		(0.0278)	(0.8391)
Lived Urban Area 1997		0.1693	0.4380		0.0230	0.9134
		(0.1174)	(1.4682)		(0.0355)	(1.9030)
Lived NE US 1997		-0.0027	-0.2757		0.0210	-0.0049
		(0.0102)	(0.2955)		(0.0227)	(0.2514)
Lived Western US 1997		0.0033	-0.5928		-0.0692	0.3357
		(0.0104)	(0.4007)		(0.0430)	(0.3465)
Lived Southern US 1997		-0.0392	-0.8340		0.1670**	0.1780
		(0.1237)	(0.5340)		(0.0824)	(0.4433)
Year of Birth		0.0121	-152.3476		-0.0012	-580.9247
		(0.0304)	(851.9050)		(0.0055)	(807.7502)
High Net Worth Avg	95.7703***			95.7703***		
	(0.3367)			(0.3366)		
Comparison Avg	92.0691***			93.9135***		
	(0.4371)			(0.4095)		
difference	3.7013***			1.8569***		
	(0.5517)			(0.5300)		
explained	3.0422***			1.2208**		
	(0.7233)			(0.5340)		
unexplained	0.6591			0.6360		
	(0.7826)			(0.6584)		
Constant			162.0564			592.9703
			(851.2093)			(807.3159)
Observations	3,138	3,138	3,138	2,790	2,790	2,790
N Comparison	1897	1897	1897	1549	1549	1549
N High Net Worth	1241	1241	1241	1241	1241	1241

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

Table A.3: Oaxaca Blinder: Belief Likelihood Military

Comparison Group VARIABLES	Low Net Worth overall	Low Net Worth explained	Low Net Worth unexplained	Mid Net Worth overall	Mid Net Worth explained	Mid Net Worth unexplained
Avg Years of Parents Schooling		0.0452	0.1199		0.0294	0.1069
		(0.0357)	(0.3808)		(0.0228)	(0.3955)
HH Net Worth ($10,000s)		0.0606	0.0367*		0.0617	-0.0664
		(0.0528)	(0.0221)		(0.0397)	(0.1007)
Parent Ever in Jail		0.0045	0.0061		0.0016	0.0051
		(0.0092)	(0.0101)		(0.0043)	(0.0095)
Parent Serve in Military		-0.0114**	-0.0079		-0.0002	-0.0481
		(0.0047)	(0.0285)		(0.0024)	(0.0302)
Mom's Age at First Birth		0.0478**	-0.1881		0.0411**	-0.2712
		(0.0227)	(0.2718)		(0.0178)	(0.2833)
% Peers Coll Plan (∼ 25 ppts)		-0.0024	-0.0068		-0.0007	-0.0316
		(0.0130)	(0.1913)		(0.0084)	(0.2014)
% Peers Cut Class (∼ 25 ppts)		0.0032	-0.0440		0.0030	-0.0328
		(0.0098)	(0.1062)		(0.0058)	(0.1046)
% Peers Sports/Clubs (∼ 25 ppts)		-0.0046	-0.1922		-0.0037	-0.1827
		(0.0050)	(0.1926)		(0.0038)	(0.2063)
% Peers in Gang (∼ 25 ppts)		0.0109	-0.0356		0.0158	0.0218
		(0.0163)	(0.1032)		(0.0103)	(0.1065)
ASVAB AFQT (10 percentile pts)		0.1456***	-0.2624**		0.0374*	-0.0303
		(0.0356)	(0.1129)		(0.0212)	(0.1218)
Ever Stole $50+ by age 18		0.0020	-0.0258		0.0009	-0.0274
		(0.0029)	(0.0199)		(0.0015)	(0.0191)
Ever Attack/harm Someone by age 18		0.0387***	0.0207		0.0202**	0.0010
		(0.0117)	(0.0307)		(0.0084)	(0.0297)
Ever had Sex by age 15		0.0058	-0.0556		0.0200*	-0.0136
		(0.0156)	(0.0346)		(0.0108)	(0.0320)
Female		-0.0304***	0.0607		0.0032	0.1182**
		(0.0103)	(0.0514)		(0.0089)	(0.0480)
Hispanic		0.0043	0.0003		0.0005	-0.0063
		(0.0169)	(0.0236)		(0.0103)	(0.0200)
Black		-0.0466**	0.0170		-0.0185	0.0272
		(0.0232)	(0.0252)		(0.0150)	(0.0209)
Lived Rural Area 1997		-0.0127	0.0514		-0.0011	0.0618
		(0.0149)	(0.0658)		(0.0024)	(0.0813)
Lived Urban Area 1997		0.0093	0.1275		0.0014	0.1470
		(0.0132)	(0.1758)		(0.0032)	(0.1840)
Lived NE US 1997		0.0006	-0.0412*		-0.0002	-0.0034
		(0.0019)	(0.0241)		(0.0008)	(0.0240)
Lived Western US 1997		-0.0002	-0.0371		-0.0054	0.0017
		(0.0007)	(0.0334)		(0.0038)	(0.0302)
Lived Southern US 1997		0.0068	-0.0887*		0.0142*	-0.0337
		(0.0099)	(0.0455)		(0.0077)	(0.0415)
Year of Birth		0.0027	81.1232		-0.0001	15.2877
		(0.0024)	(73.9985)		(0.0006)	(74.6880)
Comparison Avg	2.3342***			2.1735***		
	(0.0341)			(0.0339)		
High Net Worth Avg	2.0343***			2.0343***		
	(0.0349)			(0.0349)		
difference	0.3000***			0.1392***		
	(0.0488)			(0.0487)		
explained	0.2796***			0.2207***		
	(0.0669)			(0.0474)		
unexplained	0.0204			-0.0815		
	(0.0816)			(0.0658)		
Constant			-80.5578			-15.1128
			(73.9949)			(74.6707)
Observations	2,637	2,637	2,637	2,504	2,504	2,504
N High Net Worth	1138	1138	1138	1138	1138	1138
N Comparison	1499	1499	1499	1366	1366	1366

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

Table A.4: Oaxaca Blinder: Belief Arrest

Comparison Group VARIABLES	Low Net Worth overall	Low Net Worth explained	Low Net Worth unexplained	Mid Net Worth overall	Mid Net Worth explained	Mid Net Worth unexplained
Avg Years of Parents Schooling		-0.5315	2.4624		-0.3044	2.3912
		(0.4938)	(4.9736)		(0.2640)	(4.6804)
HH Net Worth ($10,000s)		-0.8613	-0.6117*		-0.9194*	-0.3471
		(0.7470)	(0.3665)		(0.5444)	(1.2859)
Parent Ever in Jail		0.2582*	0.2284**		-0.0153	0.1369
		(0.1394)	(0.1000)		(0.0498)	(0.0946)
Parent Serve in Military		0.0027	-0.0905		-0.0095	0.3001
		(0.0457)	(0.3589)		(0.0166)	(0.3703)
Mom's Age at First Birth		-0.0877	3.7529		0.4585**	-3.1649
		(0.3070)	(3.5127)		(0.1958)	(3.2039)
% Peers Coll Plan ($\sim$ 25 ppts)		0.1865	-3.7034		-0.0376	-1.0570
		(0.1742)	(2.5494)		(0.1074)	(2.5939)
% Peers Cut Class ($\sim$ 25 ppts)		0.4272***	0.0360		0.1814**	-0.9645
		(0.1304)	(1.2939)		(0.0741)	(1.2530)
% Peers Clubs/Sports ($\sim$ 25 ppts)		0.0027	1.0917		0.0584	-1.5624
		(0.0619)	(2.3531)		(0.0446)	(2.4182)
% Peers in Gang ($\sim$ 25 ppts)		0.6632***	1.9819		0.0458	0.4725
		(0.2370)	(1.2784)		(0.1271)	(1.2984)
ASVAB AFQT (10 percentile points)		0.6786	-0.5682		0.1107	1.1603
		(0.4463)	(1.4236)		(0.2596)	(1.4987)
Ever Stole $50+ by age 18		0.3424***	0.0197		0.1676*	-0.1691
		(0.1083)	(0.3190)		(0.0877)	(0.3069)
Ever Attack/harm Someone by age 18		0.7878***	0.6758*		0.3317***	0.1708
		(0.1673)	(0.3857)		(0.1102)	(0.3670)
Ever had Sex by age 15		0.8373***	-0.0935		0.6709***	0.2281
		(0.2051)	(0.4390)		(0.1482)	(0.4158)
Female		-0.3262***	-2.1361***		0.0384	-1.3693**
		(0.1051)	(0.6407)		(0.0850)	(0.5763)
Hispanic		0.1278	-0.3131		0.0659	-0.3270
		(0.2081)	(0.2879)		(0.1198)	(0.2510)
Black		0.1168	-0.5279		0.2393	-0.4107
		(0.2993)	(0.3467)		(0.1936)	(0.3028)
Lived Rural Area 1997		0.0382	-0.1570		0.0212	-1.4742
		(0.1695)	(0.7253)		(0.0452)	(1.0239)
Lived Urban Area 1997		-0.0145	-1.4163		-0.0098	-2.4986
		(0.1476)	(1.9373)		(0.0281)	(2.3887)
Lived NE US 1997		0.0022	-0.2880		-0.0097	-0.3572
		(0.0086)	(0.3136)		(0.0162)	(0.2967)
Lived Western US 1997		-0.0007	0.5613		0.0236	0.3278
		(0.0055)	(0.4177)		(0.0387)	(0.3732)
Lived Southern US 1997		-0.1029	0.1222		-0.1257	-0.1337
		(0.1244)	(0.5597)		(0.0920)	(0.5187)
Year of Birth		-0.0304	170.1484		-0.0065	-244.9536
		(0.0324)	(877.1799)		(0.0160)	(833.1692)
Comparison Avg	11.0901***			9.1181***		
	(0.4638)			(0.4337)		
High Net Worth Avg	7.1048***			7.1048***		
	(0.4078)			(0.4075)		
difference	3.9854***			2.0134***		
	(0.6177)			(0.5951)		
explained	2.5165***			0.9755		
	(0.8890)			(0.6149)		
unexplained	1.4689			1.0379		
	(1.0324)			(0.8117)		
Constant			-169.7059			254.6395
			(877.3648)			(833.5148)
Observations	3,138	3,138	3,138	2,790	2,790	2,790
N High Net Worth	1241	1241	1241	1241	1241	1241
N Comparison Group	1897	1897	1897	1549	1549	1549

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

Table A.5: Oaxaca Blinder: Belief Victim Violence

Comparison Group VARIABLES	Low Net Worth overall	Low Net Worth explained	Low Net Worth unexplained	Mid Net Worth overall	Mid Net Worth explained	Mid Net Worth unexplained
Avg Years of Parents Schooling		0.0715	2.8695		0.1548	1.5672
		(0.5727)	(5.9273)		(0.3436)	(5.9960)
HH Net Worth ($10,000s)		0.0922	-0.1859		0.2744	-0.1398
		(0.7722)	(0.3738)		(0.5774)	(1.4614)
Parent Ever in Jail		0.1951	-0.0422		0.0252	-0.1090
		(0.1468)	(0.1284)		(0.0529)	(0.1201)
Parent Serve in Military		-0.0000	0.0974		-0.0022	0.1169
		(0.0515)	(0.4130)		(0.0089)	(0.4215)
Mom's Age at First Birth		0.4517	2.4572		0.0914	6.7371*
		(0.3286)	(3.7862)		(0.2324)	(3.8051)
% Peers Coll Plan ($\sim$ 25 ppts)		0.1760	-3.1626		-0.1352	1.4871
		(0.1906)	(2.8077)		(0.1260)	(2.9668)
% Peers Cut Class ($\sim$ 25 ppts)		0.5165***	-0.4881		0.2134**	-1.5728
		(0.1536)	(1.5658)		(0.0889)	(1.5304)
% Peers in Clubs/Sports ($\sim$ 25 ppts)		0.0763	0.3094		0.1510**	-4.6038*
		(0.0733)	(2.7326)		(0.0634)	(2.7382)
% Peers in Gang ($\sim$ 25 ppts)		0.5816**	-1.7003		0.2065	-2.3362
		(0.2670)	(1.6741)		(0.1487)	(1.6833)
ASVAB AFQT (10 percentile pts)		-2.5899***	2.6303		-1.3878***	1.8712
		(0.5235)	(1.6504)		(0.3050)	(1.7107)
Ever Stole $50+ by age 18		0.2089**	0.0748		0.0986*	-0.0815
		(0.0813)	(0.3092)		(0.0575)	(0.2953)
Ever Attack/harm Someone by age 18		0.7696***	-0.1363		0.4825***	-0.1704
		(0.1888)	(0.4463)		(0.1321)	(0.4241)
Ever had Sex by age 15		0.6986***	0.0961		0.3282**	-0.0664
		(0.2323)	(0.4911)		(0.1515)	(0.4574)
Female		-0.0765	-2.9841***		-0.0098	-0.9076
		(0.0497)	(0.7356)		(0.0223)	(0.6666)
Hispanic		0.0162	-0.0938		-0.0137	-0.2418
		(0.2400)	(0.3466)		(0.1404)	(0.2968)
Black		0.1422	0.2203		-0.0827	0.0135
		(0.3415)	(0.3628)		(0.2125)	(0.3135)
Lived Rural Area 1997		0.4469**	-0.2416		0.0034	1.6004
		(0.2247)	(0.9698)		(0.0171)	(1.0504)
Lived Urban Area 1997		-0.2648	-2.1161		0.0251	3.2483
		(0.1933)	(2.5861)		(0.0407)	(2.4200)
Lived NE US 1997		0.0004	0.0051		-0.0141	-0.2670
		(0.0044)	(0.3422)		(0.0197)	(0.3238)
Lived Western US 1997		-0.0100	-0.0272		-0.0780	0.0701
		(0.0279)	(0.4781)		(0.0536)	(0.4377)
Lived Southern US 1997		0.0767	0.0466		0.0043	-0.0580
		(0.1426)	(0.6415)		(0.1047)	(0.6039)
Year of Birth		-0.1129**	-2,085.7601*		-0.0136	-1,466.3832
		(0.0572)	(1,074.8159)		(0.0328)	(1,022.4104)
Comparison Avg	14.8882***			12.7611***		
	(0.5145)			(0.4839)		
High Net Worth Avg	11.3433***			11.3433***		
	(0.4759)			(0.4761)		
difference	3.5450***			1.4179**		
	(0.7008)			(0.6788)		
explained	1.4664			0.3217		
	(0.9760)			(0.6680)		
unexplained	2.0786*			1.0962		
	(1.2069)			(0.9514)		
Constant			2,090.2103*			1,461.3218
			(1,074.6616)			(1,022.7639)
Observations	3,138	3,138	3,138	2,790	2,790	2,790
N High Net Worth	1241	1241	1241	1241	1241	1241
N Comparison	1897	1897	1897	1549	1549	1549

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

Table A.6: Oaxaca Blinder: Belief Pregnancy

Comparison Group VARIABLES	Low Net Worth overall	Low Net Worth explained	Low Net Worth unexplained	Mid Net Worth overall	Mid Net Worth explained	Mid Net Worth unexplained
Avg Years of Parents Schooling		0.8241*	2.9458		-0.1241	12.0696***
		(0.4595)	(4.4411)		(0.2546)	(4.2667)
HH Net Worth ($10,000s)		-0.4351	-0.1484		-0.2320	-0.3371
		(0.5002)	(0.2378)		(0.3823)	(1.1069)
Parent Ever in Jail		0.1467	0.1088		0.0413	0.1368
		(0.1314)	(0.0893)		(0.0577)	(0.0987)
Parent Serve in Military		0.0304	0.1479		0.0012	0.2970
		(0.0411)	(0.3183)		(0.0064)	(0.3017)
Mom's Age at First Birth		0.1885	-2.1540		0.2777*	-4.1393
		(0.2832)	(3.0227)		(0.1609)	(2.5914)
% Peers Coll Plans (∼ 25 ppts)		-0.0197	0.0362		0.0899	-1.9603
		(0.1628)	(2.1397)		(0.1038)	(2.2670)
% Peers Cut Class (∼ 25 ppts)		0.3132**	-1.6323		0.1004	-2.8149**
		(0.1326)	(1.2559)		(0.0624)	(1.1270)
% Peers in Clubs/Sports (∼ 25 ppts)		0.1100	-2.8480		0.0097	-0.1413
		(0.0691)	(2.1745)		(0.0386)	(2.1094)
% Peers in Gang (∼ 25 ppts)		0.7141***	1.4101		0.1714	0.3510
		(0.2556)	(1.3225)		(0.1363)	(1.3413)
ASVAB AFQT (10 percentile pts)		1.0176***	-2.7238**		0.4397*	-1.9840
		(0.3948)	(1.1970)		(0.2370)	(1.2925)
Ever Stole $50+ by age 18		0.2148***	0.4263		0.0417	-0.1515
		(0.0792)	(0.2664)		(0.0330)	(0.2375)
Ever Attack/harm Someone by age 18		0.3607**	0.4827		0.2714***	0.5130
		(0.1582)	(0.3556)		(0.1025)	(0.3305)
Ever had Sex by age 15		1.5087***	0.3076		0.9983***	0.3310
		(0.2146)	(0.4064)		(0.1592)	(0.3823)
Female		-0.1128**	-0.1557		0.0149	-0.0624
		(0.0495)	(0.5670)		(0.0331)	(0.4961)
Hispanic		0.4109**	-0.1052		0.2422**	-0.2088
		(0.1976)	(0.2651)		(0.1232)	(0.2365)
Black		0.8444***	-0.4525		0.1399	-0.6926**
		(0.2974)	(0.3306)		(0.1810)	(0.2922)
Lived Rural Area 1997		-0.1862	1.2967**		-0.0125	1.6120***
		(0.1464)	(0.6105)		(0.0268)	(0.5990)
Lived Urban Area 1997		0.1255	2.8910*		0.0251	4.1404***
		(0.1213)	(1.5654)		(0.0355)	(1.3805)
Lived NE US 1997		0.0030	-0.3021		-0.0081	-0.2465
		(0.0110)	(0.2879)		(0.0132)	(0.2355)
Lived Western US 1997		0.0072	-0.5573		-0.0313	0.3186
		(0.0203)	(0.3829)		(0.0369)	(0.3465)
Lived Southern US 1997		-0.0518	-0.0478		-0.0849	-0.0355
		(0.1191)	(0.5170)		(0.0807)	(0.4431)
Year of Birth		-0.0768*	-1,326.2211*		-0.0130	-1,233.2455*
		(0.0415)	(788.9277)		(0.0310)	(716.4666)
Comparison Avg	9.0643***			6.6869***		
	(0.4601)			(0.4139)		
High Net Worth Avg	3.7728***			3.7728***		
	(0.3125)			(0.3130)		
difference	5.2915***			2.9141***		
	(0.5562)			(0.5189)		
explained	5.9375***			2.3589***		
	(0.7343)			(0.4927)		
unexplained	-0.6460			0.5552		
	(0.8267)			(0.6814)		
Constant			1,326.6491*			1,226.8054*
			(788.7308)			(716.3481)
Observations	3,138	3,138	3,138	2,790	2,790	2,790
N High Net Worth	1241	1241	1241	1241	1241	1241
N Comparison	1897	1897	1897	1549	1549	1549

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

A.3 Supplementary Figures Chapter 2

A.3.1 Oaxaca Blinder Output: Outcomes and Beliefs

Table A.7: Oaxaca Blinder: Degree by age 30

VARIABLES	(1) overall	(2) explained	(3) unexplained	(4) overall	(5) explained	(6) unexplained
Belief: Prob Enroll Coll		0.0350***	0.1698***		0.0295***	0.0949**
		(0.0045)	(0.0402)		(0.0042)	(0.0430)
Belief: Prob Work 20+ Hrs		-0.0004	-0.0084		-0.0002	0.0058
		(0.0012)	(0.1110)		(0.0009)	(0.1225)
Belief: Prob Arrest NY		0.0006	0.0119		-0.0007	0.0057
		(0.0017)	(0.0092)		(0.0011)	(0.0096)
Belief: Prob Victim Violence		0.0031**	-0.0198*		0.0009	-0.0225*
		(0.0016)	(0.0118)		(0.0008)	(0.0123)
Belief: Prob Parent Young		-0.0046**	0.0036		-0.0001	0.0073
		(0.0019)	(0.0058)		(0.0013)	(0.0060)
Avg Yrs Parents School		0.0810***	0.4412***		0.0604***	0.2848*
		(0.0116)	(0.1333)		(0.0085)	(0.1463)
Parent Ever in Jail		-0.0014	0.0067**		-0.0000	0.0061**
		(0.0022)	(0.0032)		(0.0011)	(0.0030)
Parent Serve in Military		-0.0024*	-0.0097		-0.0010	0.0047
		(0.0014)	(0.0090)		(0.0010)	(0.0103)
Mom's Age at First Birth		0.0251***	0.0312		0.0090	0.1367
		(0.0069)	(0.0868)		(0.0057)	(0.0943)
% Peers Coll Plan ($\sim$ 25 ppts)		-0.0020	-0.0324		0.0029	-0.1149*
		(0.0036)	(0.0609)		(0.0027)	(0.0673)
% Peers Cut Class ($\sim$ 25 ppts)		0.0015	-0.0711**		0.0017	-0.0466
		(0.0028)	(0.0346)		(0.0019)	(0.0364)
% Peers Sports/Clubs ($\sim$ 25 ppts)		0.0018	0.0090		0.0012	-0.0117
		(0.0013)	(0.0616)		(0.0011)	(0.0672)
% Peers in Gang ($\sim$ 25 ppts)		0.0027	-0.0144		0.0043	-0.0068
		(0.0038)	(0.0302)		(0.0026)	(0.0316)
ASVAB AFQT (10 pct)		0.1468***	0.0279		0.1021***	-0.0303
		(0.0118)	(0.0369)		(0.0090)	(0.0419)
Ever Stole $50+ by age 18		0.0016	-0.0018		0.0009	0.0002
		(0.0010)	(0.0060)		(0.0007)	(0.0061)
Ever Attack Someone by age 18		0.0096***	-0.0049		0.0089***	0.0016
		(0.0029)	(0.0092)		(0.0027)	(0.0095)
Ever had Sex by age 15		0.0170***	-0.0330***		0.0180***	-0.0148
		(0.0043)	(0.0112)		(0.0037)	(0.0111)
Female		-0.0033**	0.0151		0.0007	0.0076
		(0.0014)	(0.0158)		(0.0013)	(0.0163)
Hispanic		-0.0110**	-0.0052		-0.0078**	-0.0100
		(0.0048)	(0.0080)		(0.0033)	(0.0073)
Black		-0.0288***	0.0067		-0.0217***	0.0024
		(0.0066)	(0.0080)		(0.0051)	(0.0073)
HH Net Worth ($10,000s)		0.0548***	-0.0169*		0.0393***	-0.0310
		(0.0204)	(0.0093)		(0.0152)	(0.0336)
High Net Worth Avg	0.5617***			0.5617***		
	(0.0149)			(0.0150)		
Comparison Avg	0.1508***			0.2809***		
	(0.0088)			(0.0120)		
difference	0.4109***			0.2808***		
	(0.0173)			(0.0192)		
explained	0.3246***			0.2462***		
	(0.0238)			(0.0190)		
unexplained	0.0863***			0.0345		
	(0.0281)			(0.0235)		
Constant			26.8635			18.1537
			(31.3742)			(33.4972)
Observations	2,760	2,760	2,760	2,501	2,501	2,501
N Comparison	1658	1658	1658	1399	1399	1399
N High Net Worth	1102	1102	1102	1102	1102	1102

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

Table A.8: Oaxaca Blinder: Work 20+ hrs in 2010

Comparison Group VARIABLES	Low Net Worth overall	Low Net Worth explained	Low Net Worth unexplained	Mid Net Worth overall	Mid Net Worth explained	Mid Net Worth unexplained
Belief: Prob Enroll Coll		0.0089	0.0500		0.0127***	-0.0202
		(0.0057)	(0.0483)		(0.0040)	(0.0519)
Belief: Prob Work 20+ Hrs		0.0057***	-0.2055*		0.0009	-0.0801
		(0.0021)	(0.1156)		(0.0010)	(0.1245)
Belief: Prob Arrest NY		0.0009	-0.0031		0.0016	0.0036
		(0.0024)	(0.0097)		(0.0015)	(0.0102)
Belief: Prob Victim Violence		-0.0010	0.0196		-0.0012	0.0070
		(0.0020)	(0.0127)		(0.0010)	(0.0128)
Belief: Prob Parent Young		-0.0065**	0.0010		-0.0013	0.0065
		(0.0028)	(0.0062)		(0.0018)	(0.0066)
Avg Yrs Parents School		0.0118	-0.0976		0.0028	-0.0395
		(0.0131)	(0.1396)		(0.0082)	(0.1461)
Parent Ever in Jail		0.0032	-0.0032		0.0018	-0.0022
		(0.0032)	(0.0032)		(0.0015)	(0.0030)
Parent Serve in Military		-0.0003	0.0034		-0.0004	0.0114
		(0.0015)	(0.0103)		(0.0005)	(0.0109)
Mom's Age at First Birth		0.0139*	-0.0269		0.0009	0.1218
		(0.0084)	(0.0981)		(0.0061)	(0.1007)
% Peers Coll Plan ($\sim$ 25 ppts)		-0.0072	-0.0260		0.0042	-0.2080***
		(0.0047)	(0.0689)		(0.0030)	(0.0729)
% Peers Cut Class ($\sim$ 25 ppts)		-0.0001	0.0301		-0.0021	0.0034
		(0.0035)	(0.0374)		(0.0021)	(0.0382)
% Peers Sports/Clubs ($\sim$ 25 ppts)		0.0022	-0.1236*		0.0001	-0.0776
		(0.0017)	(0.0696)		(0.0011)	(0.0722)
% Peers in Gang ($\sim$ 25 ppts)		0.0124**	-0.0371		0.0003	-0.0773**
		(0.0059)	(0.0381)		(0.0034)	(0.0392)
ASVAB AFQT (10 percentile points)		0.0391***	-0.0673		0.0290***	-0.0962**
		(0.0128)	(0.0413)		(0.0078)	(0.0433)
Ever Stole $50+ by age 18		-0.0002	-0.0085		0.0011	0.0013
		(0.0012)	(0.0068)		(0.0009)	(0.0070)
Ever Attack Someone by age 18		0.0083**	-0.0088		0.0048*	-0.0126
		(0.0039)	(0.0108)		(0.0029)	(0.0107)
Ever had Sex by age 15		0.0160***	0.0009		0.0107***	-0.0008
		(0.0054)	(0.0123)		(0.0039)	(0.0119)
Female		0.0048***	0.0406**		-0.0008	0.0311*
		(0.0019)	(0.0179)		(0.0014)	(0.0172)
Hispanic		-0.0152***	0.0006		-0.0051	0.0057
		(0.0059)	(0.0084)		(0.0034)	(0.0072)
Black		0.0187**	-0.0049		0.0013	-0.0144*
		(0.0086)	(0.0098)		(0.0055)	(0.0085)
HH Net Worth ($10,000s)		0.0071	0.0029		0.0106	-0.0375
		(0.0197)	(0.0100)		(0.0150)	(0.0376)
High Net Worth Avg	0.7849***			0.7849***		
	(0.0124)			(0.0124)		
Comparison Avg	0.6248***			0.7119***		
	(0.0119)			(0.0121)		
difference	0.1601***			0.0730***		
	(0.0172)			(0.0173)		
explained	0.1210***			0.0752***		
	(0.0241)			(0.0173)		
unexplained	0.0391			-0.0022		
	(0.0295)			(0.0239)		
Constant			0.0071			19.2404
			(36.2634)			(37.0821)
Observations	2,760	2,760	2,760	2,501	2,501	2,501
N Comparison	1658	1658	1658	1399	1399	1399
N High Net Worth	1102	1102	1102	1102	1102	1102

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

Table A.9: Oaxaca Blinder: Military

Comparison Group VARIABLES	Low Net Worth overall	Low Net Worth explained	Low Net Worth unexplained	Mid Net Worth overall	Mid Net Worth explained	Mid Net Worth unexplained
Belief: Prob Enroll Coll		0.0016	-0.0076		-0.0003	0.0060
		(0.0027)	(0.0277)		(0.0020)	(0.0317)
Belief: Prob Work 20+ Hrs		0.0003	0.0364		0.0000	0.0486
		(0.0008)	(0.0471)		(0.0005)	(0.0657)
Belief: Prob Arrest NY		0.0020*	0.0020		-0.0001	-0.0021
		(0.0012)	(0.0054)		(0.0008)	(0.0060)
Belief: Prob Victim Violence		-0.0006	0.0056		0.0001	0.0112
		(0.0010)	(0.0080)		(0.0004)	(0.0084)
Belief: Prob Parent Young		0.0003	-0.0083**		0.0018	-0.0050
		(0.0015)	(0.0039)		(0.0012)	(0.0041)
Belief: Likelihood Join Military		-0.0060***	0.0495**		-0.0043**	0.0111
		(0.0017)	(0.0220)		(0.0018)	(0.0235)
Avg Yrs of Parents School		0.0047	-0.0761		-0.0036	0.0341
		(0.0071)	(0.0851)		(0.0050)	(0.0917)
Parent Ever in Jail		-0.0004	-0.0003		0.0004	0.0006
		(0.0016)	(0.0019)		(0.0008)	(0.0018)
Parent Serve in Military		0.0033***	0.0015		0.0006	-0.0064
		(0.0013)	(0.0067)		(0.0012)	(0.0080)
Mom's Age at First Birth		-0.0076*	-0.0212		-0.0029	-0.0443
		(0.0044)	(0.0561)		(0.0040)	(0.0644)
% Peers Coll Plan ($\sim$ 25 ppts)		-0.0060**	0.0438		-0.0026	0.0121
		(0.0026)	(0.0437)		(0.0019)	(0.0487)
% Peers Cut Class ($\sim$ 25 ppts)		-0.0010	0.0436*		-0.0007	0.0413
		(0.0019)	(0.0229)		(0.0014)	(0.0256)
% Peers Sports Clubs ($\sim$ 25 ppts)		0.0007	-0.0189		0.0003	-0.0038
		(0.0009)	(0.0421)		(0.0008)	(0.0477)
% Peers in Gang ($\sim$ 25 ppts)		-0.0001	-0.0387*		-0.0004	-0.0435*
		(0.0028)	(0.0211)		(0.0024)	(0.0236)
ASVAB AFQT (10 percentile pts)		0.0258***	-0.0419*		0.0149***	-0.0357
		(0.0072)	(0.0237)		(0.0047)	(0.0266)
Ever Stole $50+ by age 18		0.0001	-0.0070*		0.0006	-0.0003
		(0.0006)	(0.0042)		(0.0006)	(0.0042)
Ever Attack Someone by age 18		-0.0018	0.0130*		-0.0042**	0.0033
		(0.0022)	(0.0071)		(0.0020)	(0.0074)
Ever had Sex by age 15		-0.0003	-0.0022		-0.0029	-0.0073
		(0.0031)	(0.0079)		(0.0025)	(0.0079)
Female		0.0041**	-0.0041		-0.0008	-0.0047
		(0.0016)	(0.0110)		(0.0015)	(0.0111)
Hispanic		-0.0024	-0.0089*		-0.0002	-0.0067
		(0.0032)	(0.0048)		(0.0023)	(0.0045)
Black		-0.0059	-0.0036		0.0019	0.0033
		(0.0048)	(0.0059)		(0.0036)	(0.0051)
HH Net Worth ($10,000s)		-0.0204*	0.0033		-0.0118	-0.0471*
		(0.0114)	(0.0042)		(0.0091)	(0.0254)
High Net Worth Avg	0.0721***			0.0721***		
	(0.0082)			(0.0081)		
Comparison Avg	0.0486***			0.0863***		
	(0.0059)			(0.0079)		
difference	0.0236**			-0.0142		
	(0.0101)			(0.0114)		
explained	-0.0064			-0.0178*		
	(0.0134)			(0.0102)		
unexplained	0.0300*			0.0036		
	(0.0180)			(0.0156)		
Constant			4.5927			-12.0556
			(19.3034)			(21.0695)
Observations	2,330	2,330	2,330	2,252	2,252	2,252
N Comparison	1318	1318	1318	1240	1240	1240
N High Net Worth	1012	1012	1012	1012	1012	1012

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

Table A.10: Oaxaca Blinder: Arrest

Comparison Group VARIABLES	Low Net Worth overall	Low Net Worth explained	Low Net Worth unexplained	Mid Net Worth overall	Mid Net Worth explained	Mid Net Worth unexplained
Belief: Prob Enroll Coll		0.0161***	-0.0065		0.0083**	0.0031
		(0.0053)	(0.0468)		(0.0037)	(0.0509)
Belief: Prob Work 20+ Hrs		-0.0004	-0.0058		0.0004	-0.0735
		(0.0016)	(0.1084)		(0.0010)	(0.1208)
Belief: Prob Arrest NY		0.0079***	-0.0083		0.0048**	-0.0047
		(0.0026)	(0.0102)		(0.0020)	(0.0104)
Belief: Prob Victim Violence		0.0016	-0.0027		-0.0004	-0.0160
		(0.0018)	(0.0118)		(0.0007)	(0.0120)
Belief: Prob Parent Young		0.0056**	-0.0120*		0.0040**	-0.0097
		(0.0027)	(0.0072)		(0.0020)	(0.0075)
Avg Yrs Parents School		0.0019	0.0573		0.0167**	-0.1459
		(0.0121)	(0.1306)		(0.0079)	(0.1387)
Parent Ever in Jail		0.0077**	-0.0055*		0.0022	-0.0058*
		(0.0030)	(0.0032)		(0.0015)	(0.0031)
Parent Serve in Military		-0.0009	0.0085		-0.0002	0.0083
		(0.0014)	(0.0095)		(0.0004)	(0.0103)
Mom's Age at First Birth		-0.0020	0.0610		0.0012	0.0299
		(0.0077)	(0.0903)		(0.0056)	(0.0925)
% Peers Coll Plan ($\sim$ 25 ppts)		-0.0046	-0.0279		-0.0081***	0.0767
		(0.0043)	(0.0645)		(0.0030)	(0.0700)
% Peers Cut Class ($\sim$ 25 ppts)		0.0040	-0.0267		0.0021	-0.0332
		(0.0033)	(0.0355)		(0.0020)	(0.0362)
% Peers Sports/Clubs ($\sim$ 25 ppts)		0.0007	0.0031		0.0007	-0.0087
		(0.0015)	(0.0615)		(0.0011)	(0.0658)
% Peers in Gang ($\sim$ 25 ppts)		-0.0042	0.0609*		0.0004	0.0799**
		(0.0054)	(0.0344)		(0.0032)	(0.0358)
ASVAB AFQT (10 pct)		0.0282**	-0.0480		0.0044	0.0109
		(0.0119)	(0.0395)		(0.0075)	(0.0434)
Ever Stole $50+ by age 18		0.0096***	-0.0062		0.0059*	0.0004
		(0.0030)	(0.0073)		(0.0034)	(0.0074)
Ever Attack Someone by age 18		0.0263***	-0.0147		0.0239***	-0.0003
		(0.0046)	(0.0114)		(0.0044)	(0.0114)
Ever had Sex by age 15		0.0373***	0.0092		0.0254***	0.0151
		(0.0058)	(0.0124)		(0.0046)	(0.0120)
Female		-0.0110***	-0.0307*		0.0015	0.0039
		(0.0037)	(0.0176)		(0.0028)	(0.0165)
Hispanic		-0.0087	-0.0057		-0.0042	-0.0073
		(0.0057)	(0.0089)		(0.0033)	(0.0077)
Black		-0.0192**	0.0028		-0.0071	0.0071
		(0.0077)	(0.0083)		(0.0052)	(0.0073)
HH Net Worth ($10,000s)		0.0084	-0.0090		0.0022	-0.0044
		(0.0212)	(0.0133)		(0.0149)	(0.0371)
Comparison Avg	0.3788***			0.3481***		
	(0.0119)			(0.0127)		
High Net Worth Avg	0.2577***			0.2577***		
	(0.0132)			(0.0132)		
difference	0.1211***			0.0904***		
	(0.0178)			(0.0183)		
explained	0.1020***			0.0873***		
	(0.0250)			(0.0185)		
unexplained	0.0190			0.0031		
	(0.0288)			(0.0230)		
Constant			83.5020**			64.6415*
			(34.2687)			(36.8982)
Observations	2,760	2,760	2,760	2,501	2,501	2,501
N High Net Worth	1102	1102	1102	1102	1102	1102
N Comparison	1658	1658	1658	1399	1399	1399

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

Table A.11: Oaxaca Blinder: Incarceration

Comparison Group VARIABLES	Low Net Worth overall	Low Net Worth explained	Low Net Worth unexplained	Mid Net Worth overall	Mid Net Worth explained	Mid Net Worth unexplained
Belief: Prob Enroll Coll		0.0066*	-0.0082		0.0026	0.0034
		(0.0034)	(0.0284)		(0.0023)	(0.0314)
Belief: Prob Work 20+ Hrs		-0.0017	0.1337**		-0.0001	0.0769
		(0.0011)	(0.0655)		(0.0007)	(0.0780)
Belief: Prob Arrest NY		0.0031	-0.0075		0.0023*	-0.0032
		(0.0020)	(0.0085)		(0.0013)	(0.0088)
Belief: Prob Victim Violence		0.0002	0.0094		-0.0006	0.0009
		(0.0013)	(0.0077)		(0.0006)	(0.0076)
Belief: Prob Parent Young		0.0026	0.0105**		0.0019	0.0136***
		(0.0021)	(0.0042)		(0.0015)	(0.0046)
Avg Yrs Parent School		0.0017	0.1159		0.0146***	-0.0837
		(0.0076)	(0.0753)		(0.0049)	(0.0797)
Parent Ever in Jail		0.0076***	-0.0010		0.0022*	-0.0012
		(0.0025)	(0.0027)		(0.0012)	(0.0026)
Parent Serve in Military		-0.0005	-0.0049		-0.0001	-0.0072
		(0.0009)	(0.0059)		(0.0002)	(0.0059)
Mom's Age at First Birth		0.0030	-0.0655		-0.0033	0.0129
		(0.0047)	(0.0525)		(0.0034)	(0.0539)
% Peers Coll Plan ($\sim$ 25 ppts)		-0.0020	-0.0261		-0.0012	-0.0238
		(0.0027)	(0.0366)		(0.0018)	(0.0413)
% Peers Cut Class ($\sim$ 25 ppts)		-0.0003	-0.0254		-0.0007	-0.0359*
		(0.0020)	(0.0199)		(0.0012)	(0.0205)
% Peers Sports/Clubs ($\sim$ 25 ppts)		-0.0007	0.0974***		-0.0004	0.1039**
		(0.0010)	(0.0377)		(0.0007)	(0.0413)
% Peers in Gang ($\sim$ 25 ppts)		0.0003	0.0115		0.0010	0.0185
		(0.0039)	(0.0204)		(0.0021)	(0.0209)
ASVAB AFQT (10 pct)		0.0211***	-0.0486**		0.0080*	-0.0269
		(0.0071)	(0.0221)		(0.0043)	(0.0239)
Ever Stole $50+ by age 18		0.0049***	-0.0007		0.0029*	0.0027
		(0.0017)	(0.0055)		(0.0017)	(0.0057)
Ever Attack Someone by age 18		0.0076***	-0.0113		0.0072***	-0.0078
		(0.0026)	(0.0072)		(0.0021)	(0.0070)
Ever had Sex by age 15		0.0090***	0.0019		0.0074***	0.0072
		(0.0033)	(0.0073)		(0.0024)	(0.0070)
Female		-0.0044***	-0.0391***		0.0006	-0.0220**
		(0.0016)	(0.0101)		(0.0011)	(0.0090)
HISPANIC		-0.0072**	-0.0067		-0.0025	-0.0028
		(0.0036)	(0.0049)		(0.0019)	(0.0040)
BLACK		-0.0097*	-0.0096*		-0.0018	-0.0023
		(0.0051)	(0.0054)		(0.0033)	(0.0046)
HH Net Worth ($10,000s)		0.0029	-0.0116		-0.0063	0.0178
		(0.0139)	(0.0129)		(0.0076)	(0.0214)
Comparison Avg	0.1049***			0.0893***		
	(0.0075)			(0.0076)		
High Net Worth Avg	0.0463***			0.0463***		
	(0.0063)			(0.0063)		
difference	0.0587***			0.0431***		
	(0.0098)			(0.0099)		
explained	0.0473***			0.0358***		
	(0.0155)			(0.0095)		
unexplained	0.0114			0.0072		
	(0.0179)			(0.0125)		
Constant			31.7404*			19.0572
			(17.2141)			(19.9345)
Observations	2,760	2,760	2,760	2,501	2,501	2,501
N High Net Worth	1102	1102	1102	1102	1102	1102
N Comparison	1658	1658	1658	1399	1399	1399

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

Table A.12: Oaxaca Blinder: Pregnancy

Comparison Group VARIABLES	Low Net Worth overall	Low Net Worth explained	Low Net Worth unexplained	Mid Net Worth overall	Mid Net Worth explained	Mid Net Worth unexplained
Belief: Prob Enroll Coll		0.0137***	-0.0268		0.0084***	-0.0309
		(0.0049)	(0.0358)		(0.0030)	(0.0375)
Belief: Prob Work 20+ Hrs		0.0020	-0.0016		0.0006	0.0126
		(0.0017)	(0.0770)		(0.0008)	(0.0815)
Belief: Prob Arrest NY		-0.0006	0.0057		-0.0016	-0.0016
		(0.0021)	(0.0066)		(0.0012)	(0.0069)
Belief: Prob Victim Violence		-0.0008	-0.0060		0.0002	-0.0026
		(0.0017)	(0.0095)		(0.0006)	(0.0094)
Belief: Prob Parent Young		0.0035	0.0016		0.0046**	0.0092*
		(0.0027)	(0.0051)		(0.0019)	(0.0055)
Avg Yrs Parents School		0.0224**	-0.0912		0.0139**	-0.0848
		(0.0103)	(0.0969)		(0.0058)	(0.0958)
Parent Ever in Jail		0.0070**	0.0032		0.0005	0.0020
		(0.0030)	(0.0019)		(0.0012)	(0.0019)
Parent Serve in Military		0.0008	-0.0001		0.0005	-0.0102
		(0.0011)	(0.0070)		(0.0006)	(0.0068)
Mom's Age at First Birth		0.0232***	-0.1820***		0.0034	-0.0009
		(0.0064)	(0.0672)		(0.0042)	(0.0668)
% Peers Coll Plan ($\sim$ 25 ppts)		0.0078**	-0.0298		0.0033	-0.0211
		(0.0037)	(0.0472)		(0.0022)	(0.0491)
% Peers Cut Class ($\sim$ 25 ppts)		0.0028	0.0155		0.0008	0.0015
		(0.0028)	(0.0256)		(0.0015)	(0.0251)
% Peers Sports/Clubs ($\sim$ 25 ppts)		0.0021	-0.0882**		-0.0014	0.0401
		(0.0014)	(0.0449)		(0.0009)	(0.0450)
% Peers in Gang ($\sim$ 25 ppts)		0.0044	-0.0213		0.0017	-0.0242
		(0.0051)	(0.0260)		(0.0028)	(0.0272)
ASVAB AFQT (10 percentile pts)		0.0149	-0.0348		0.0140***	-0.0573**
		(0.0092)	(0.0278)		(0.0050)	(0.0271)
Ever Stole $50+ by age 18		-0.0002	-0.0008		0.0005	0.0043
		(0.0010)	(0.0051)		(0.0006)	(0.0051)
Ever Attack Someone by age 18		0.0053*	-0.0024		0.0045**	-0.0013
		(0.0031)	(0.0076)		(0.0022)	(0.0073)
Ever had Sex by age 15		0.0368***	0.0219**		0.0185***	0.0034
		(0.0051)	(0.0092)		(0.0036)	(0.0089)
Female		0.0095***	0.1072***		-0.0010	0.0551***
		(0.0032)	(0.0126)		(0.0019)	(0.0116)
HISPANIC		0.0013	-0.0040		0.0043*	0.0025
		(0.0045)	(0.0058)		(0.0024)	(0.0048)
BLACK		0.0078	-0.0057		0.0080*	0.0025
		(0.0069)	(0.0068)		(0.0044)	(0.0058)
HH Net Worth ($10,000s)		-0.0003	0.0133*		0.0074	-0.0180
		(0.0095)	(0.0069)		(0.0069)	(0.0276)
Comparison Avg	0.2527***			0.1658***		
	(0.0107)			(0.0099)		
High Net Worth Avg	0.0499***			0.0499***		
	(0.0066)			(0.0066)		
difference	0.2028***			0.1159***		
	(0.0125)			(0.0119)		
explained	0.1686***			0.0936***		
	(0.0155)			(0.0103)		
unexplained	0.0342*			0.0223		
	(0.0192)			(0.0145)		
Constant			-11.6451			19.1523
			(23.9931)			(24.4825)
Observations	2,760	2,760	2,760	2,501	2,501	2,501
N High Net Worth	1102	1102	1102	1102	1102	1102
N Comparison	1658	1658	1658	1399	1399	1399

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

Appendix B

Appendix to Chapter 3

B.1 Data Construction and Summary Statistics

From the NLSY97 I use data on parental education, household net worth, self reported probabilities of school enrollment and obtaining a degree by age 30[1], labor market earnings, schooling activities, financial assistance, and parental transfers. Additionally I use demographic information like race, ethnicity, gender, census region, urban/rural categorical variables, gender, as well as year of birth. Table 11 shows the resulting sample size after dropping missing variables.

I use measures of cognitive human capital and non-cognitive human capital 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. For youth missing transcript data, I impute transcript GPA. 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.

[1] For individuals that are missing Probability of Degree, I impute it using the quantitative model equivalent to probability of degree; probability of enrollment times probability of continuation; using consecutive year estimates of probability of enrollment.

Table B.1: Observations Lost at Each Stage of Sample Selection

Criteria	(1) Observations Lost	(2) Observations Remaining
Total NLSY97		8984
Drop missing parent education and HH net worth	2542	6442
Drop missing belief probability of degree/enroll and continuation	1450	4992
Drop missing educational attainment/college enrollment	1201	3791
Drop missing ASVAB math verbal scores	587	3204
Drop missing adverse behavior young age	676	2528
Drop missing race/ethnicity, year of birth, census region, urban/rural	91	2437
Drop missing high school peers with college plans	27	2410
Drop missing financial aid or GPA while enrolled	152	2258
Drop missing average lifetime earnings	125	2133

For parental education I take the average of mother's and father's years of schooling if both parents education level is in the data. If only one parent is in the data then I use that parent's years of schooling to measure parental education I bottom code at 8 years of schooling and top code at 16 years of schooling. For household net worth, I use the parent's reported household net worth at the start of the survey, before agents enroll in college. For individuals that do not have parental reports of net worth recorded, I impute household net worth using the individual youth's report.

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[2].

Since youth born between 1983-1984 were not asked for probability of degree by age 30 while in high school, I used a variable College Outcome Belief that is equal to self reported probability of degree by age 30 for youth born before 1982 and self reported probability of enrollment in college for youth born after 1982. Combining these two variables was done to increase sample size while still capturing relative optimism and pessimism among youth. This variable is used in the outcomes regressions Table 1 and Table 3, as well as in the estimation of the quantitative model where beliefs about own ability are a function of this belief measure.

As shown in appendix A.7 additional tables. The College Outcome Belief effect is towards the center of the often higher effect of Probability of Degree belief and Probability of Enrollment. The difference in the coefficient of the College Outcome Belief variable compared to the other two belief variables is no more than 0.04 at a measure of 1, which will likely lead to little bias. Future specifications will control for any bias introduced through the construction of this variable by adding year of birth controls.

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

Table B.2: 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 B.3: 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

B.2 Supplementary Analysis

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 B.4: 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 15: 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 B.5: 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 16: 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 B.6: 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 17: 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 B.7: 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 18: 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 B.8: 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).

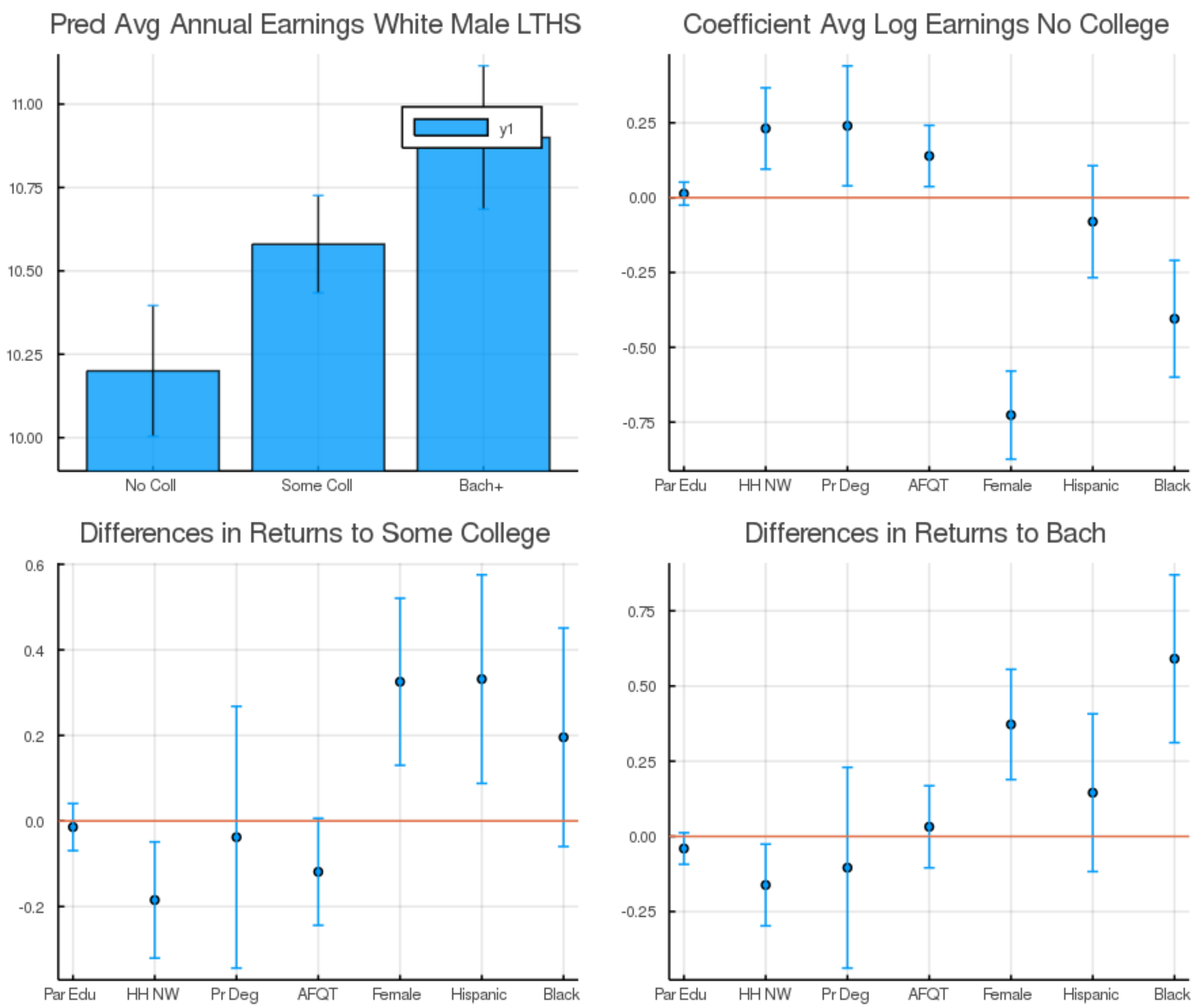

Figure B.1: Shows predicted average earnings from Table 17 in top left panel, while other three panels plot coefficients to provide scale for the results.

B.3 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 $\text{Prob}(s \geq 16)$.

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

B.4 Finite Mixture Model Results

Table 19: Funding by Demographic: External Estimate

	OLS	OLS
VARIABLES	log Family Aid	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 B.9: 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 20: 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 B.10: 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 21: 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 B.11: Shows the results from the finite mixture model for human capital variables. High Type is a binary variable if agent is high type.

Table 22: 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 B.12: 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.

B.5 Indirect Inference: Targeted vs Simulated Moments

Table 23: Indirect Inference OLS Targets

VARIABLES	(1) Enrolled Data	(2) Enrolled Sim	(3) Continue Data	(4) 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
			(0.0478)	(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 B.13: 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 24: 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 B.14: Shows the full list of 16 parameters estimated by indirect inference

B.6 Mismatch by Net Worth, Parental Edu, Race, and Ethnicity

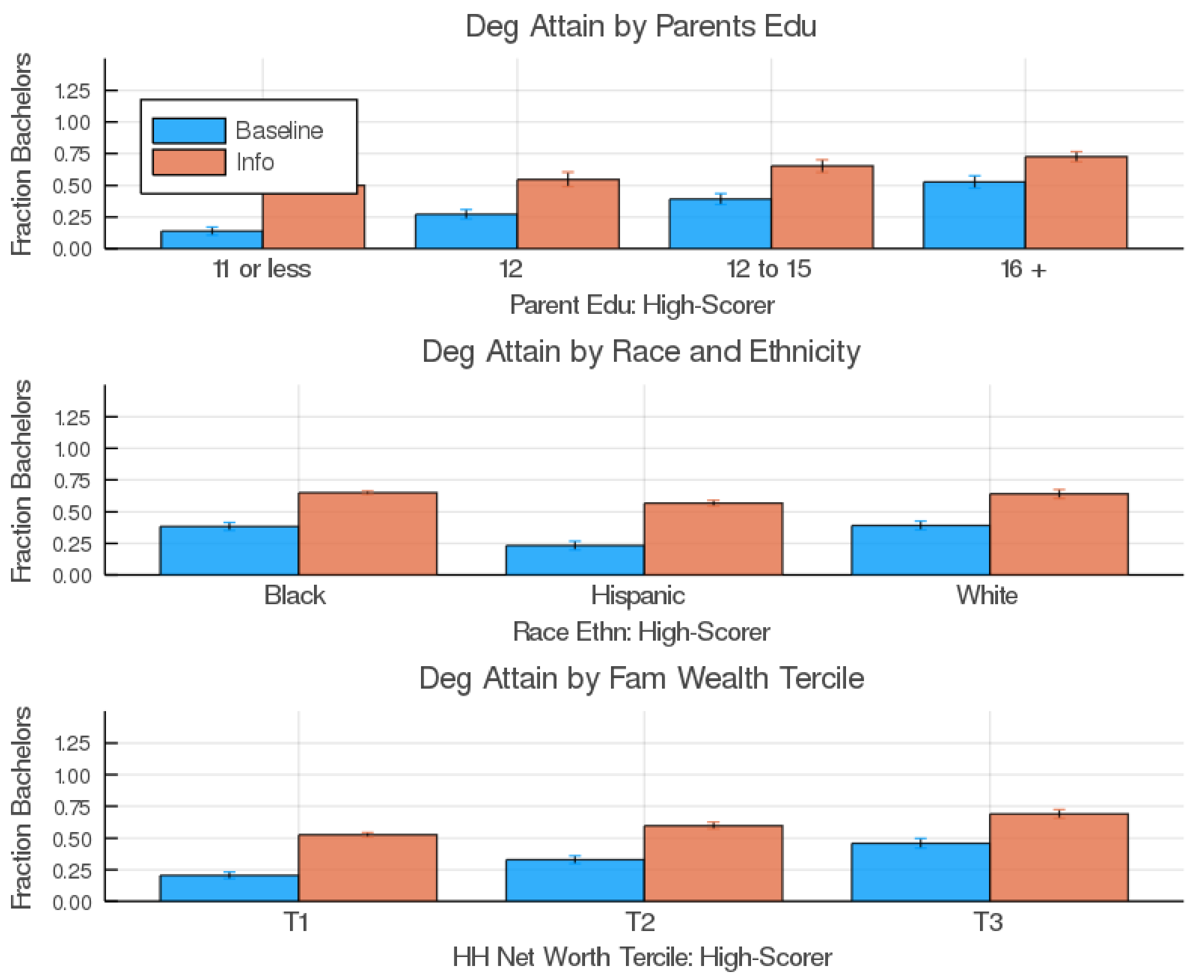

Figure B.2: Shows difference in BA attainment under baseline model and under scenario where youth know their true type with certainty. This graph looks at predicted High Scorers by demographic group.

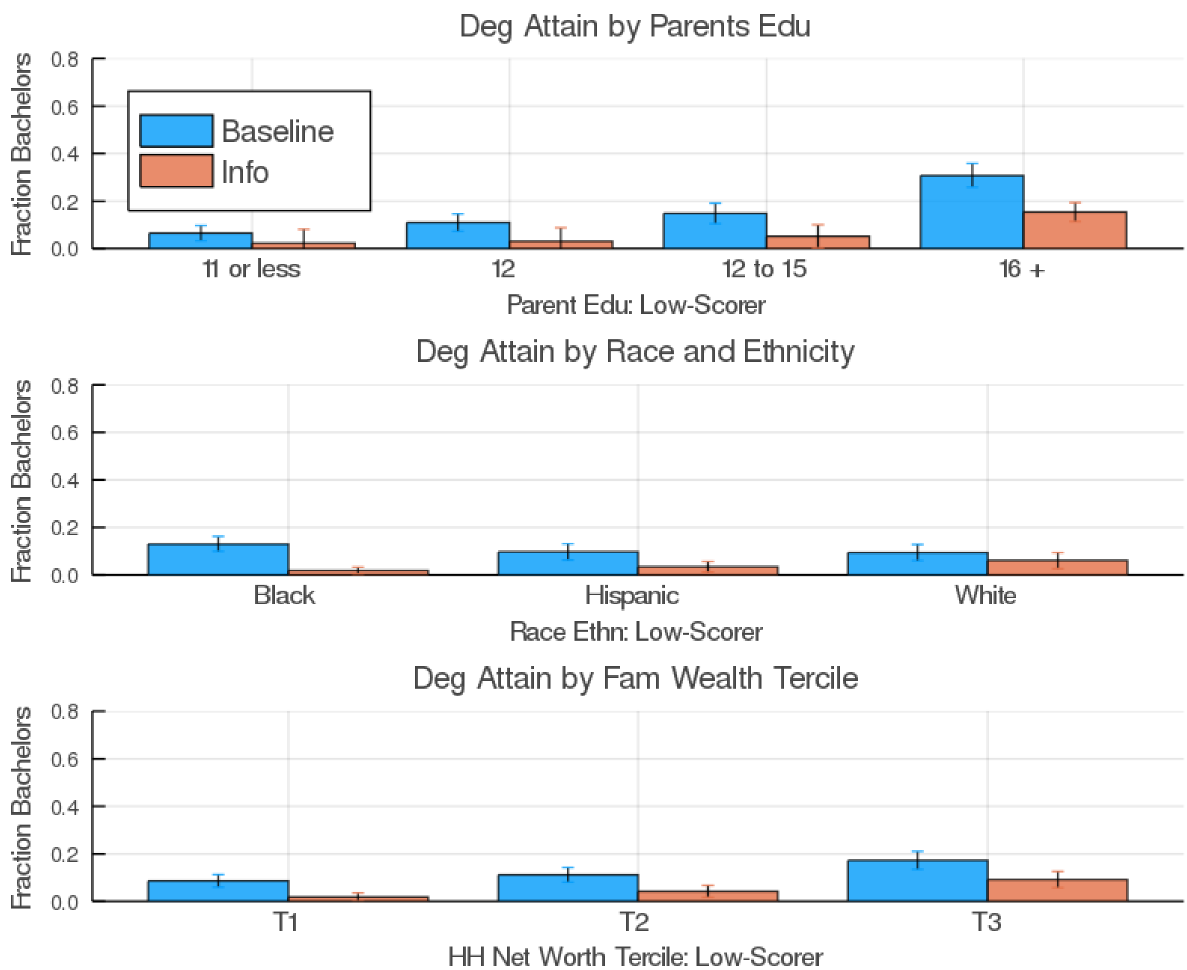

Figure B.3: Shows difference in BA attainment under baseline model and under scenario where youth know their true type with certainty. This graph looks at predicted Lower Scorers by demographic group.

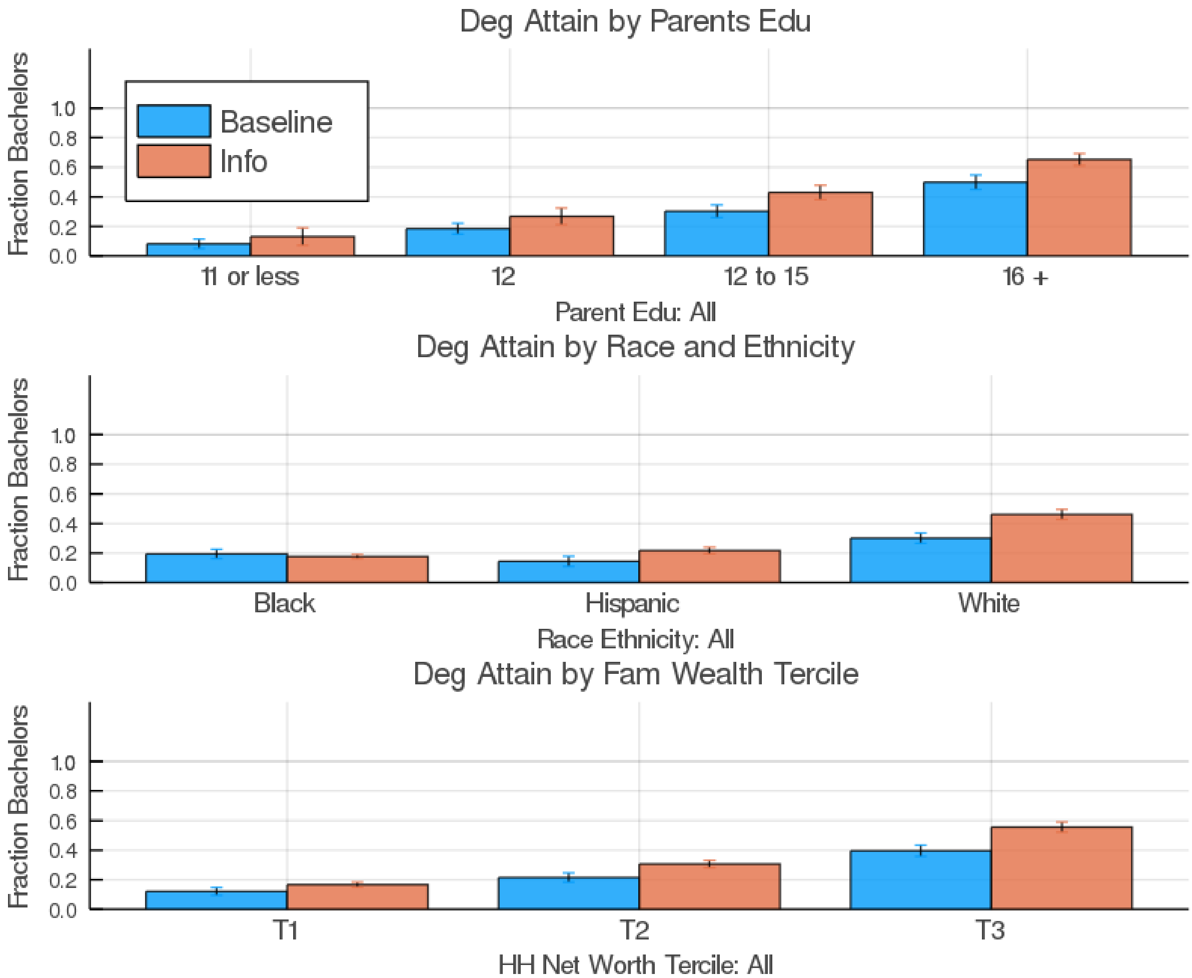

Figure B.4: Shows difference in BA attainment under baseline model and under scenario where youth know their true type with certainty. This graph looks at all youth regardless of scoring type by demographic group.

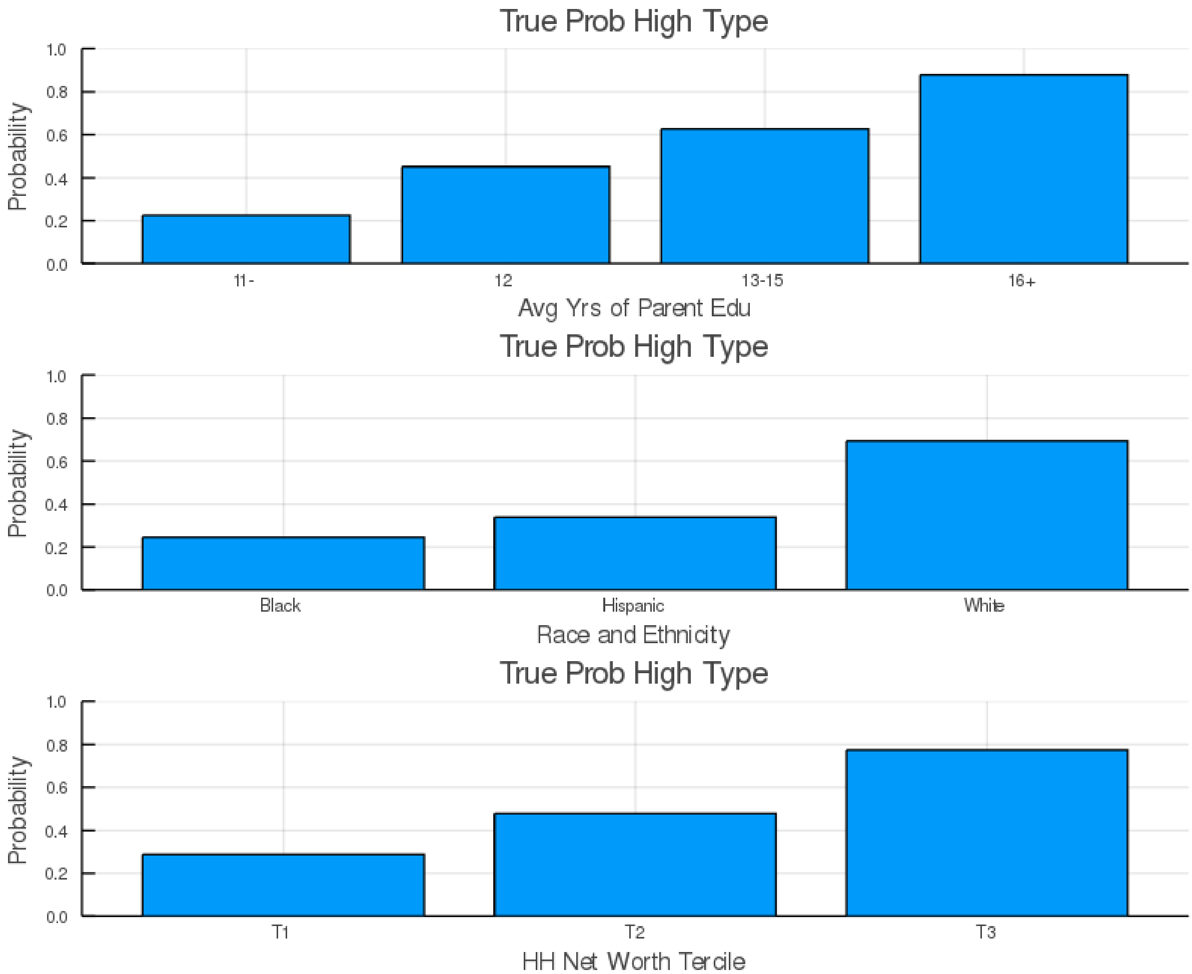

Figure B.5: Shows the estimated fraction of high-scorers by demographic background from the finite mixture model.

B.7 Additional Tables

VARIABLES	(1) Ever Enrolled	(2) Ever Enrolled	(3) Ever Enrolled	(4) Ever Enrolled
Avg Parent Education	0.0292***	0.0300***	0.0278***	0.0293***
	(0.0052)	(0.0071)	(0.0071)	(0.0052)
HH Net Worth ($1000s)	0.0001***	0.0001	0.0001**	0.0001***
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
ASVAB AFQT	0.0055***	0.0051***	0.0054***	0.0055***
	(0.0004)	(0.0005)	(0.0006)	(0.0004)
Belief_Var	0.3226***			
	(0.0346)			
Prob Degree		0.4294***		
		(0.0516)		
Prob Enroll			0.2959***	
			(0.0433)	
Born After 82 X Prob Enroll				0.3046***
				(0.0406)
Born Before 82 X Prob Degree				0.3551***
				(0.0521)
Female	0.0831***	0.0695***	0.0870***	0.0817***
	(0.0175)	(0.0236)	(0.0244)	(0.0176)
Hispanic	0.0812***	0.0824**	0.0680*	0.0822***
	(0.0302)	(0.0413)	(0.0396)	(0.0303)
Black	0.1700***	0.1465***	0.1831***	0.1701***
	(0.0266)	(0.0367)	(0.0365)	(0.0266)
Constant	-0.2972***	-0.3428***	-0.3564***	-0.3204***
	(0.0873)	(0.1224)	(0.1143)	(0.0928)
Geography Controls	Yes	Yes	Yes	Yes
Birth Year	Yes	Yes	Yes	Yes
Non Cognitive Controls	Yes	Yes	Yes	Yes
Observations	2,133	1,143	1,139	2,133
R-squared	0.3499	0.3792	0.3444	0.3502

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

Table B.15: Shows the difference in coefficients by using different measures of beliefs about education outcomes

	(1)	(2)	(3)	(4)
VARIABLES	Bachelors Ever	Bachelors Ever	Bachelors Ever	Bachelors Ever
Avg Parent Education	0.0375***	0.0277***	0.0449***	0.0377***
	(0.0056)	(0.0077)	(0.0077)	(0.0056)
HH Net Worth ($1000s)	0.0002***	0.0003***	0.0002**	0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ASVAB AFQT	0.0057***	0.0056***	0.0055***	0.0056***
	(0.0004)	(0.0005)	(0.0006)	(0.0004)
Belief_Var	0.2151***			
	(0.0283)			
Prob Degree		0.3147***		
		(0.0445)		
Prob Enroll			0.1739***	
			(0.0351)	
Born After 82 X Prob Enroll				0.1864***
				(0.0328)
Born Before 82 X Prob Degree				0.2670***
				(0.0458)
Female	0.0847***	0.0650**	0.0957***	0.0825***
	(0.0186)	(0.0258)	(0.0252)	(0.0187)
Hispanic	0.0535*	-0.0029	0.0911**	0.0551*
	(0.0286)	(0.0394)	(0.0396)	(0.0286)
Black	0.1487***	0.1463***	0.1356***	0.1489***
	(0.0256)	(0.0361)	(0.0343)	(0.0256)
Constant	-0.6214***	-0.5570***	-0.6850***	-0.6584***
	(0.0770)	(0.1007)	(0.1050)	(0.0793)
Geography Controls	Yes	Yes	Yes	Yes
Birth Year	Yes	Yes	Yes	Yes
Non Cognitive Controls	Yes	Yes	Yes	Yes
Observations	2,133	1,143	1,139	2,133
R-squared	0.3612	0.3720	0.3619	0.3619

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

Table B.16: Shows the difference in coefficients by using different measures of beliefs about education outcomes

VARIABLES	(1) Continue Coll	(2) Continue Coll	(3) Continue Coll	(4) Continue Coll
Avg Parent Education	0.0429***	0.0239**	0.0545***	0.0428***
	(0.0069)	(0.0094)	(0.0096)	(0.0069)
HH Net Worth ($1000s)	0.0001**	0.0002**	0.0000	0.0001*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ASVAB AFQT	0.0034***	0.0029***	0.0036***	0.0034***
	(0.0006)	(0.0007)	(0.0008)	(0.0006)
Avg College GPA	0.1788***	0.1900***	0.1688***	0.1787***
	(0.0152)	(0.0203)	(0.0210)	(0.0152)
Belief_Var	0.2262***			
	(0.0498)			
Prob Degree		0.3469***		
		(0.0813)		
Prob Enroll			0.1743***	
			(0.0603)	
Born After 82 X Prob Enroll				0.2031***
				(0.0584)
Born Before 82 X Prob Degree				0.2686***
				(0.0855)
Total Govt/Inst Aid ($1000s)	0.0057**	0.0089**	0.0029	0.0055**
	(0.0027)	(0.0039)	(0.0031)	(0.0027)
Total Family Aid ($1000s)	0.0072**	0.0050	0.0082	0.0072**
	(0.0035)	(0.0040)	(0.0058)	(0.0035)
College_STUDLOAN_TTL	-0.0071**	-0.0102*	-0.0030	-0.0070**
	(0.0034)	(0.0054)	(0.0044)	(0.0035)
Female	0.0397*	0.0146	0.0660**	0.0386
	(0.0238)	(0.0325)	(0.0329)	(0.0238)
Hispanic	0.0594	-0.0318	0.1055*	0.0607
	(0.0382)	(0.0515)	(0.0540)	(0.0383)
Black	0.1797***	0.1755***	0.1620***	0.1799***
	(0.0353)	(0.0489)	(0.0478)	(0.0353)
Constant	-1.0271***	-0.9545***	-1.0609***	-1.0600***
	(0.1213)	(0.1720)	(0.1589)	(0.1309)
Geography Controls	Yes	Yes	Yes	Yes
Birth Year	Yes	Yes	Yes	Yes
Non Cognitive Controls	Yes	Yes	Yes	Yes
Observations	1,467	799	771	1,467
R-squared	0.3238	0.3374	0.3388	0.3241

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

Table B.17: Shows the difference in coefficients by using different measures of beliefs about education outcomes