Is College Worth It For Me?

Beliefs, Access to Funding, and Inequality in Higher Education Outcomes

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Motivation

- Gaps bachelor's attainment (BA) for high achievers (top quartile ASVAB AFQT).
    - Race: White 64%; Black 59%; Hispanic 52%.
    - HH Net Worth: Top Tercile 71%; Bottom Tercile 42%.
    - Parent Education: Bachelors 80%; High school or less 42%.

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- Role of credit constraints, rising tuition, and funding well studied.

  (Lochner & Monge Naranjo 2012, Dynarski 2003, Carneiro & Heckman 2002).
- Recent work suggests important role for information frictions.

  (Dynarski, Michelmore, Libassi, & Owen 2021; Hoxby & Turner 2015; Stinebrickner & Stinebrickner 2012; Bettinger, Long, Oreopoulos, & Sanbonmatsu. 2012).

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- Why beliefs differ by demographic group?

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  -Uncertainty regarding ability to perform well in presence of shocks.

  (DeLuca, Papageorge, Boselovic, Gershenson, Gray, Nerenberg, Sausedo, & Young 2021; Evans, William, Kearney, Perry, & Sullivan 2020)

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- Why information frictions important?
  -Generate inequality but also mismatch, growth, and suggests less costly policies.

  (Hsieh, Hurst, Klenow, Jones 2019)

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1. To what extent do information frictions generate mismatch in higher education across demographic groups?
   - Measured by changes in BA with complete information.

2. How much do differences in beliefs about own success (ability) explain BA gaps across demographic groups,for high ability youth?

3. Which policy counterfactual is more effective at decreasing overall gaps in BA?
   - Targeted info and funding only to high ability low SES.
   - Free college for all.
   - Better info for everyone.

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- Estimate a standard dynamic discrete education choice model, where
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- **Objective Type Probability:** Externally, econometrician can estimate using education and labor market outcomes.
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- **Subjective Type Probability:** Internally, estimate using model since agents use beliefs for decisions.
    - Leverage survey beliefs of college outcomes as noisy measure for model beliefs.

Answer to Research Question:

1. Information frictions lead to significant mismatch for all groups and ability types.
   - Low ability types too optimistic, over investment.
   - High ability types too pessimistic, under investment.

Answer to Research Question:

2. Beliefs role generating BA gaps varies across groups of high ability type. Relative to high-SES White youth, beliefs explain
   - 49% of overall Hispanic gap, Statistically Significant .
   - 38% of overall low-SES gap, Statistically Significant.
   - 33% of overall Black gap, **Not** Statistically Significant.

Answer to Research Question:

3. Targeted info and funding policy to high ability low SES.
   - Most effective at closing overall gaps (25-42%).
   - Decreases mismatch (30%).
   - Potentially less costly.

Contribution to the literature

1. **Structural Education Models**

   ⋆ Relax rational expectations prior using data and model to estimate prior.

   Heckman, Cunha, & Navarro 2005; Navarro & Zhou 2017; Arcidiacono, Aucejo, Maurel & Ransom 2016 .

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   - ⋆ Document beliefs role in high ability inequality, policy effects on several measures.

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3. **Empirical Literature**

   ⋆ Document background correlated to beliefs, beliefs correlated to education.

   Dynarski, Libassi, Michelmore & Owen 2018; Hoxby & Turner 2012, Bettinger, Long, Oreopoulos, & Sanbonmatsu 2012, Stinebrickner & Stinebrickner 2012; 2014a; Wiswall & Zafar 2015, DeLuca, Papageorge, Boselovic, Gershenson, Gray, Nerenberg, Sausedo, & Young 2021

Data

- Discuss data characteristics.
- Discuss empirical patterns to be interpreted by model.

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- Use NLSY97, US cohort born 1980-1984, over-samples Black, Hispanic.

Summary Statistics Race | Summary Statistics Par Edu | Sample Selection

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  1. See high school student. Observe,
     - background (parent education, wealth, race, ethnicity, peer plans).
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   - Funding for college (family, college, government financial aid).
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3. See their labor market earnings over lifecycle.

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Data Patterns that Inform the Model

- Controlling for important variables (human capital, access to resources, etc.)

  1. Optimism about own college outcomes strongly related to background.
  2. More optimism about college outcomes strongly related to actual outcomes.
  3. Less optimistic youth less likely to persist with medium grades.

Fact 1: Optimism related to background

Table: Measured Beliefs

VARIABLES	(OLS) Prob Enroll (pct points)
Avg Parent Education	2.56***
	(0.39)
Pct Peers College Plans About 25%	7.42
	(5.43)
Pct Peers College Plans About 50%	9.62*
	(5.02)
Pct Peers College Plans About 75%	13.79***
	(5.04)
Pct Peers College Plans More than 90%	16.56***
	(5.08)
HH Net Worth ($100,000s)	1.014***
	(0.281)
ASVAB AFQT	00.22***
	(0.03)
Geography, Birth Year, Race, Ethnicity, Gender	Yes
Non Cognitive	Yes
Observations	2,133

- All else equal, student parents bachelor's degree more optimistic by about 12 percentage points than student parents high school diploma.

Fact 2: Optimism related to outcomes

Table: College Outcomes

VARIABLES	(OLS) Ever Enrolled	(OLS) Bachelors Attained	(OLS) Complete College
Prob Enroll (10 pct point)	0.032***	0.022***	0.022***
	(0.003)	(0.003)	(0.005)
Avg Parent Education	0.0292***	0.0375***	0.0427***
	(0.0048)	(0.0056)	(0.0070)
HH Net Worth ($100,000s)	0.01**	0.02***	0.01*
	(0.004)	(0.005)	(0.005)
ASVAB AFQT	0.0055***	0.0057***	0.0035***
	(0.0004)	(0.0004)	(0.0006)
College GPA			0.1803***
			(0.0152)
Total Govt/Inst Aid ($1000s)			0.0058**
			(0.0027)
Total Fam Aid ($1000s)			0.0075**
			(0.0035)
Geography, Birth Year, Race, Ethnicity, Gender	Yes	Yes	Yes
Non Cognitive, Student Loans	Yes	Yes	Yes
Observations	2,133	2,133	1,467

- All else equal, student that's 10 percent more optimistic 3 percentage points more likely to enroll and 2 percentage points more likely to obtain bachelor's.

Fact 3: Belief and Grade Interaction

Table 3: Non Continuation Interacted with GPA

VARIABLES	(OLS) Exit College
Prob Enroll (10 pct point)	0.008
	(0.00543)
GPA 2.0-3.0	-0.1513*
	(0.0859)
GPA > 3.0	-0.3431***
	(0.0929)
Prob Enroll X GPA 2.0-3.0	-0.026**
	(0.01021)
Prob Enroll X GPA > 3.0	-0.023**
	(0.01092)
Parent Education	-0.0179**
	(0.0089)
Household Net Worth ($100,000s)	-0.003
	(0.0007)
Geography, Birth Year, Race, Ethnicity, Gender	Yes
Cognitive and Non cognitive Controls	Yes
Student Aid and Loans	Yes
Observations	1,028
R-squared	0.2576

- All else equal, student that's 10 percent more optimistic 3 percentage points less likely to exit after medium grades.

Model

1. Provide overview of model.

2. Discuss model predictions.

Model Ingredients

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- Allow for returns to some college w_s, and bachelor's $w_c(\tau)$ independent of type.

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- Objective probability $P_{true,i}$ that $\tau_i = \tau_h$.
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- No restriction that $P_i = P_{true,i}$.

Belief Updating

- Beliefs updated after realizing GPA g_k for $k = l, m, h$ by Bayes Rule.

$$P'(g_k, P) = \frac{P \cdot \pi(g_k, \tau_h)}{P \cdot \pi(g_k, \tau_h) + (1 - P) \cdot \pi(g_k, \tau_l)}$$

- Where $\pi(g_k, \tau_h) = Prob(g_k | \tau = \tau_h)$

Update Graph

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- **Stage 2: $t = 2$ Continuation** College student i continuation decision.
  - After experience, realizes shock $\vec{\varepsilon}_{2,i}$, gains info GPA g_i, updates $P'(g_i, P_i)$.
  - Then given $P'(g_i, P_i)$, $f_{2,i}$, $\vec{\varepsilon}_{2,i}$ makes continue decision then borrows $b_{3,i}$.

    Stage 2 Value Function

Three Stage problem

- **Stage 1: $t = 1$ Enrollment** High school senior i college decision.
  - Knows labor market w_n, w_s, net costs $f_{t,i}$, shock $\vec{\varepsilon}_{1,i}$, distribution $\vec{\varepsilon}_{2,i}$.
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    Stage 2 Value Function

- **Stage 3: $t = 3, \ldots, 24$ Work** Graduate works, pays debt, learns τ_i and if college worth it.

  Stage 3 Worker's Problem

Model Implications

- More optimism and lower costs lead to more school.
  - **Enroll Decision**: Holding all else constant probability of enrollment is weakly increasing in P_i, and weakly decreasing in $f_{t,i}$, $t = 1, 2$.
    Enrollment
  - **Continue decision**: Holding all else constant continuation is weakly increasing in P_i, weakly decreasing in $f_{2,i}$.
- Cross sectional differences in $P_{true,i}$ affect exit through grades.
  - **Exit response to grades**: Holding all else constant, if g_h provides a better signal for $\tau_i = \tau_h$ then continuation probability is weakly greater with g_h than with g_m or, g_l.
    Continuation

Model Estimation

1. Discuss external procedure.
2. Discuss internal procedure.
3. Discuss model fit.

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- **External Estimate** $P_{true,i}$ by observing earnings, grades, human capital scores. Additionally estimate:
  - Funding by race, gender, ethnicity, wealth, parental education OLS.
    Funding by Demographic
  - Earnings $w_n, w_s, w_c(\tau)$, grade distribution $\pi(g, \tau)$, finite mixture model.

    (Hai & Heckman 2017)

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- **Internally Estimate** P_i by matching data decisions and model decision via indirect inference. Additionally estimate
  - Tuition sticker price, with financial assistance gives $f_{t,i}$.
  - Non-pecuniary utility parameters $\mu(\tau)$ and $\vec{\varepsilon}_{t,i}$ t= 1,2.

Preset Parameters

Table: Preset Parameters

Parameter	Set Value	Description
β	0.94	Discount rate
σ	2.0	Coefficient of Rel Risk Aversion
$(1+r)$	β^{-1}	Interest rate
T	24	Number 2 year periods lifecycle
$B_{c,1}$	\$16,600	College Borrowing limit pd 1
$B_{c,2}$	\$35,600	College Borrowing limit pd 2
b_0	\$0.00	Starting Assets

- Set student loan limit to average student loan 2000-2004.

(Abbot Gallipoli, Meghir, and Violante 2016)

External Estimation Continued

- Get $P_{true,i}$ by assuming following provide info on $\tau_i \in \{\tau_l, \tau_h\}$,

    1. Vector of human capital measures and college GPA g_i. $\vec{Z}_i$. Hum Cap Grades
    2. Average log earnings w_{i,s_i} given school s_i . Earnings School

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- Given τ_i and s_i likelihood of observing $(\vec{Z}_i, w_i, g_i)$ is given by

$$\phi(\vec{Z}_i, w_{i,s}, g_i; \tau_i, \vec{X}_i, s_i)$$

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- Need share of $\tau_i = \tau_h$ by demographic characteristics $\vec{X}_i$ given by

$$\lambda(\tau_h; \vec{X}_i) = Prob(\tau = \tau_h | \vec{X}_i) = \frac{exp(\vec{X}_i \vec{\beta}_p)}{1 + exp(\vec{X}_i \vec{\beta}_p)} \tag{10}$$

External Estimation Continued

- Then solving for maximum likelihood

$$\max \sum_i \ln[\lambda(\tau_h; \vec{X}_i)\phi(\vec{Z}_i, w_i, g_i; \tau_h, \vec{X}_i, s_i) + (1 - \lambda(\tau_h; \vec{X}_i))\phi(\vec{Z}_i, w_i, g_i; \tau_h, \vec{X}_i, s_i)]$$

FMM Type Share FMM Human Capital FMM Grades-Earnings

External Estimation Continued

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- Provides estimate of objective $P_{true,i}$ used to simulate grades and counterfactuals

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

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- Also provides
  1. Value of $w_n, w_s, w_c(\tau)$, through $\mathbb{E}[w_{i,s}|\tau]$. Predicted Earnings
  2. Conditional grade probability $\pi(g, \tau_i)$. Grades by Type
  3. Share of τ_h by demographics $\lambda(\tau_h, \vec{X}_i)$. Fraction High

FMM Type Share FMM Human Capital FMM Grades-Earnings

Internally Estimated Parameters

- Main object, distribution of subjective P_i being τ_h

$$P = \gamma_{p,0} + \gamma_{p,b}\text{NLSY Belief} + \gamma_{p,h}\text{Par HSD} + \gamma_{p,s}\text{Par SCOL} + \gamma_{p,s}\text{Par Bach} + \sigma_p \eta_p$$

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- Additionally, given preset, external parameters, estimate
  1. Location scale Type 1 EV shocks: race, first gen. ($\vec{\varepsilon}_t$).
  2. Non pecuniary utility by τ_i, $\mu_c(\tau_i)$.
  3. Sticker price of tuition, $tuit_t$ to get $f_{t,i} = tuit_t - fund_i$.

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- Main object, distribution of subjective P_i being τ_h

$$P = \gamma_{p,0} + \gamma_{p,b}\text{NLSY Belief} + \gamma_{p,h}\text{Par HSD} + \gamma_{p,s}\text{Par SCOL} + \gamma_{p,s}\text{Par Bach} + \sigma_p \eta_p$$

- Additionally, given preset, external parameters, estimate
  1. Location scale Type 1 EV shocks: race, first gen. ($\vec{\varepsilon}_t$).
  2. Non pecuniary utility by τ_i, $\mu_c(\tau_i)$.
  3. Sticker price of tuition, $tuit_t$ to get $f_{t,i} = tuit_t - fund_i$.

- Via indirect inference solve for vector Γ 16 parameters minimizes difference in 17 OLS coefficients.

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

Internally Estimated Target Moments

- Target enrollment.

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

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

- Target continuation.

$$Continue_i = \beta_{C,0} + \beta_{C,g_m} 1(g_i = g_m) + \beta_{C,g_h} 1(g_i = g_h) + \beta_{C,F_2} T2(fund_i) + \beta_{C,F_2} T3(fund_i)$$

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

- Belief parameters identified through $\beta_{E,B}, \beta_{C,g_m}, \beta_{C,g_h}$. Target Fit | Key Parameter Results

Model Fit with Estimated Parameters

- Matches bachelor's attainment by demographic group, and college non continuation by GPA.

Model Fit Demographic BA Non Cont GPA

Model Fit with Estimated Parameters

- Matches bachelor's attainment by demographic group, and college non continuation by GPA.
  Model Fit | Demographic BA | Non Cont GPA

- For main results focus on difference in BA, between White high SES vs Black, Hispanic, low SES.

Model Estimation

1. To what extent do information frictions generate mismatch in higher education across demographic groups?

2. How much do differences in beliefs about success (ability) type play in generating BA gaps across groups for high ability youth?

3. Which policy is more effective and efficient at narrowing overall inequality?

Question 1: Information Frictions and Mismatch

- Mismatch from information friction.

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- Mismatch from information friction.
  - Average beliefs P_i by type τ_i wrong with respect to objective probability $P_{true,i}$.

Pred vs Belief

Question 1: Information Frictions and Mismatch

- Mismatch from information friction.
  - Average beliefs P_i by type τ_i wrong with respect to objective probability $P_{true,i}$.
    Pred vs Belief
  - Significant mismatch for considered groups.
    Mismatch Type

Question 2: How Much Beliefs Explain Gaps

- Estimation results show:
  - High ability-high SES white youth, more optimistic, more funding.

Difference Causal Variables

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- **Research Question 2:** How much do differences in beliefs about success (ability) type play in generating BA gaps across groups for high ability youth?
  - Sequentially set beliefs, then funding to average White high SES for high type.

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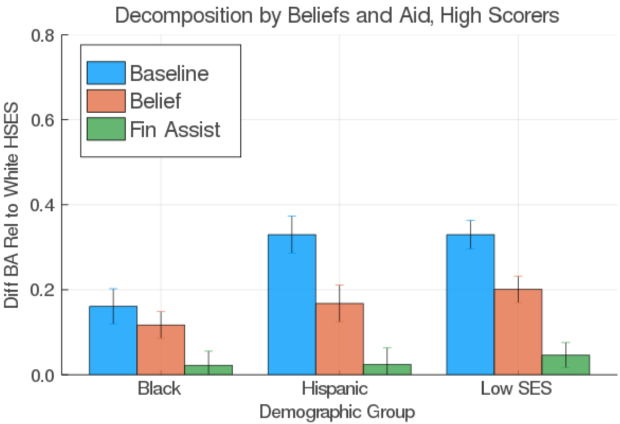
  - High ability-high SES white youth, more optimistic, more funding.
    Difference Causal Variables
- **Research Question 2:** How much do differences in beliefs about success (ability) type play in generating BA gaps across groups for high ability youth?
  - Sequentially set beliefs, then funding to average White high SES for high type.
  - Also see what role differences in funding play in generating inequality.

Decomposition: High ability type



- Significant role of beliefs for Hispanic, low-SES, funding significant for all three.

Decomposition Table

Question 3: Policy Counterfactuals

- Which policy is more effective and efficient at decreasing overall gaps in BA?

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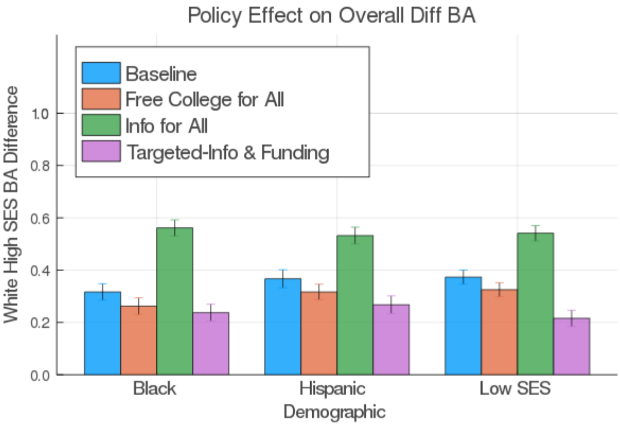
Question 3: Policy Counterfactuals

- Which policy is more effective and efficient at decreasing overall gaps in BA?
  - Efficiency: College Mismatch - proportion who change BA decision with knowledge of type.
  - Cost Effectiveness: Benefit to cost ratio, average net benefit per recipient.
- Policies:
  1. Targeted info and funding only to high ability low SES.
  2. Free college for all (Keep family funding same, set tuition to zero).
  3. Better info for everyone (Give everyone $P_{true,i}$).

Effect of Policy on Overall Inequality



- Free College for All and targeted policy decrease inequality.
- Better information for all increases inequality.

Mismatch Aggregate Policy Table

Mismatch Policy

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

Policy	% Pop Mismatched Overall	% Pop Mismatched High-Type	% Pop Mismatched Low-Type
Baseline	27.1 % (1.834)	21.3 % (1.505)	5.8 % (1.222)
Free College For All	30.5% (1.107)	21.5 % (1.296)	9.1 % (1.395)
Better Info for All	4.4 % (0.300)	4.1 % (0.284)	0.3 % (0.086)
Targeted: Info and Funding	19.1% (1.214)	13.3 % (0.946)	5.9% (1.201)

Cost Effectiveness

Table 11: Cost Effectiveness

Policy	Benefit-Cost Ratio	Average Net Benefit Recipient
Free College For All	13.78	$260,000
	(1.386)	(28,433)
Targeted: Info and Funding	31.27	$750,000
	(2.014)	(50,984)

Main Findings

1. Beliefs: Significant 38-49 % of bachelor's gap; Hispanic, low SES high type.
    - Can't reject a belief effect of zero for Black high type.
    - However financial resources significant for all (45 -50%).
2. Targeted subsidies and info most efficient at closing overall gaps.
    - Close gaps between 25-42% depending on demographic group.
    - Efficient: decrease mismatch by decreasing underinvestment.
    - Cost Effective, if cost is less then $490,000 per beneficiary.
    - Universal policies exhibit equity/efficiency trade off.

Conclusion

- Information frictions lead to underinvestment in higher education for high ability youth from underrepresented backgrounds.
- Providing info and funding effective for decreasing inequality and increasing efficiency, two examples
  - HAIL- recruiting letter and promised funding (Cost:$ 10 student).
    (Dynarski, Michelmore, Libassi & Owen 2021)
  - Stay the Course - assignment of case managers (Cost: $4384).
    (Evans, Perry, Kearney & Sullivan 2020)
- Still important role for human capital, may interact with parents beliefs.
  (List, Pernaudet & Suskind 2021)

Patterns in the Data: Full Sample

Table: 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

Data

Patterns in the Data: Full Sample

Table: 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

Data

Sample Selection

Table: 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

Data

Patterns in the Data: Beliefs

Table: Measured Beliefs

VARIABLES	(1) Pct Chance Deg by 30	(2) Prob Enroll
Parent Edu	0.0267***	0.0282***
	(0.0046)	(0.0058)
HH Net Worth	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)
Hispanic	0.0435	0.1174**
	(0.0268)	(0.0323)
Black	0.0978***	0.1071***
	(0.0246)	(0.0312)
Geography & Birth Year Controls	Yes	Yes
Non Cognitive Controls	Yes	Yes
Observations	1,143	1,139
R-squared	0.2614	0.2304

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

Empirical Facts Fin Aid Reg

Patterns in the Data: Financial Assistance

Table: Financial Assistance

VARIABLES	(1) Any Family Aid	(2) Total Fam Aid	(3) Any Govt/Inst Aid	(4) Total Govt/Inst 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 & Birth Year Controls	Yes	Yes	Yes	Yes
Non Cognitive Controls	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
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Belief Regression

Patterns in the Data: Earnings

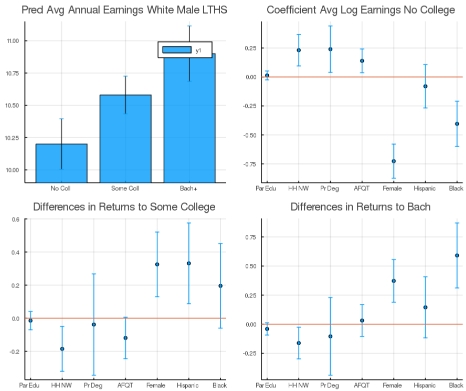
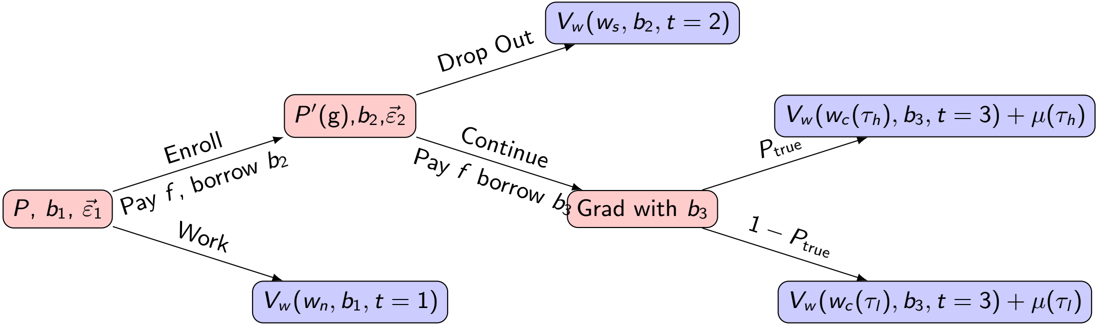


Figure: Earnings by EDU and Differences in Log Returns to School

Empirical Facts

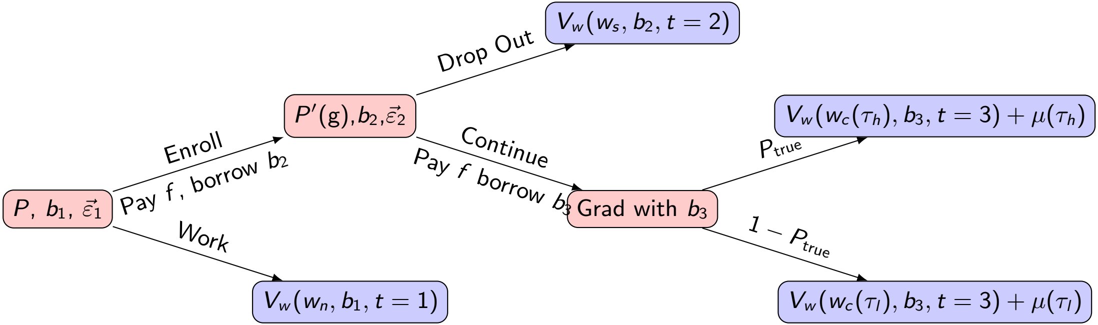
Timeline



- Stage 1, (t=1): Begin belief P, asset b_1, taste shocks $\vec{\varepsilon}_1$; enroll or work and earn w_n.

Model Inputs Environment

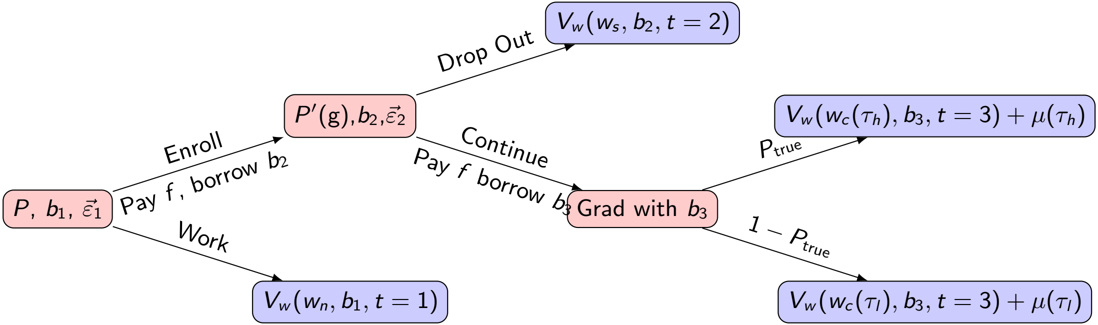
Timeline



- Stage 1, (t=1): Begin belief P, asset b_1, taste shocks $\vec{\varepsilon}_1$; enroll or work and earn w_n.
- Stage 2 (t=2): Realize GPA g, Update to $P'(g)$, debt b_2, taste shocks $\vec{\varepsilon}_2$; continue or work and earn w_s.

Model Inputs | Environment

Timeline



- Stage 1, (t=1): Begin belief P, asset b_1, taste shocks $\vec{\varepsilon}_1$; enroll or work and earn w_n.
- Stage 2 (t=2): Realize GPA g, Update to $P'(g)$, debt b_2, taste shocks $\vec{\varepsilon}_2$; continue or work and earn w_s.
- Stage 3, (t=3,...,T): Complete College with debt b_3,Prob P_{true} earn $w_c(\tau_h)$, (1-P_{true}) earn $w_c(\tau_l)$.

Model Inputs Environment

Stage 1: Enrollment Decision

- Begin with belief P, net tuition f_1, know f_2, assets b_1 , and non-pecuniary utility $\vec{\varepsilon}_1 = (\varepsilon_{c,1}, \varepsilon_{w,1})$.

$$(3) \qquad V_1(P, f_1, f_2, b_1, \vec{\varepsilon}_1) = \max\{V_w(w_n, b_1, 1) + \varepsilon_{w,1}, V_{c,1}(P, f_1, f_2, b_1) + \varepsilon_{c,1}\}$$

$$s.t.$$

$$V_{c,1}(P, f_1, f_2, b_1) = \max_{b_2 \geq -\tilde{B}_{s,1}} \left[u(Rb_1 - f_1 - b_2) + \beta \mathbb{E}_{g,\varepsilon}(V_2(P'(g, P), f_2, b_2, \vec{\varepsilon}_2)) \,|P\,\right]$$

- $\varepsilon_{c,1}, \varepsilon_{w,1}$ are iid Type 1 Extreme Value and $\tilde{B}_1^s > \tilde{B}_1(w)$

Intuition

Stage 2: Continue/Exit Decision

- Begin with belief P', net tuition f_2, debt b_2 , and non-pecuniary utility $\vec{\varepsilon}_2 = (\varepsilon_{c,2}, \varepsilon_{w,2})$.

$$(5) \quad V_2(P', f_2, b_2, \vec{\varepsilon}_2) = \max\{V_w(w_s, b_2, 2) + \varepsilon_{w,2}, V_{c,2}(P', f_2, b_2) + \epsilon_{c,2}\}$$

$$s.t.$$

$$V_{c,2}(P', f_2, b_2) = \max_{b_3 \geq -\tilde{B}_{s,2}} [u(Rb_2 - f_2 - b_3) + \beta(P'[V_w(w_c(\tau_h), b_3) + \mu(\tau_h)]$$

$$+ \quad (1 - P')[V_w(w_c(\tau_l), b_3) + \mu(\tau_l)]) \quad]$$

- $\varepsilon_{c,2}, \varepsilon_{w,2}$ are iid Type 1 Extreme Value and $\tilde{B}_2^s > \tilde{B}_2(w)$

Intuition

Stage 3: Workers Problem

- Work problem depends on age t.

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

- Per period utility is CRRA

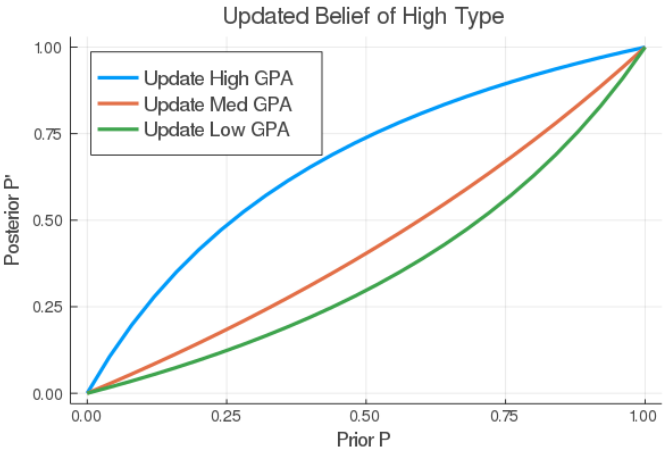
$$(2) \qquad u(c) = \frac{c^{1-\gamma}-1}{1-\gamma}$$

- Borrowing constraints

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

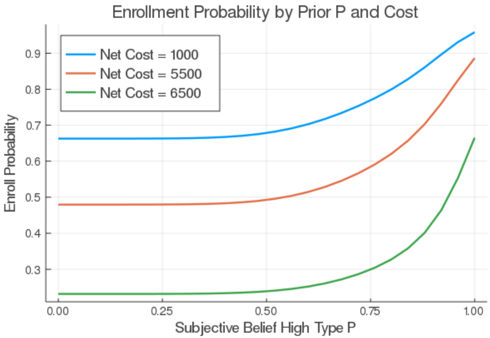
Intuition

Update Graph



Update Rule

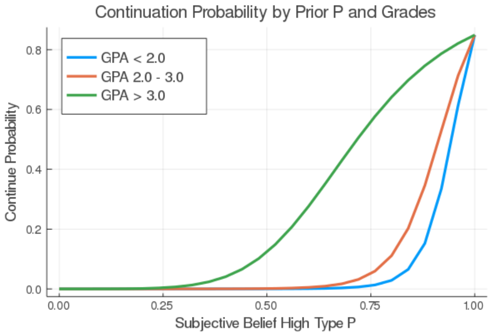
Model Predictions



- Probability of enrollment increasing in optimism P_i and funding (decreasing $f_{t,i}$).

Model Implications

Model Predictions



- Probability of continuation increasing in optimism P_i and better grade realization.

Model Implications

Model Predictions

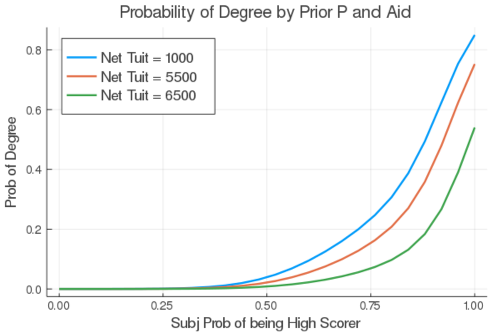


Figure: Model predicted probability of Bachelor's attainment, enrollment and completion, by Net Tuition and Prior Belief of being "successful"

Model Implications

External: Human Capital and Grades

- Use $j \in 1, \ldots, 7$ measures of human capital that are functions of τ_i.
  - Cognitive human capital: continuous ASVAB math and verbal knowledge scores.
  - Non-cognitive human capital: binary risky behavior, violence, theft, sex young ages.

$$Z^*_{i,j} = \alpha_{z,j,0} + \alpha_{z,j,\tau} 1(\tau_i = \tau_h) + \varepsilon_{z,j} \quad j \in \{1, \ldots, 7\}$$

$$Z_{i,j} = \begin{cases} Z^*_{i,j} & \text{if } Z_{i,j} \text{ is continuous} \\ 1(Z^*_{i,j} > 0) & \text{if } Z_{i,j}, \text{ is binary} \end{cases}$$

- Conditional probability of $g \in \{g_l, g_m, g_h\}$ given τ.

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

External Spec

External: Earnings and Schooling Selection

- Earnings given s_i and τ

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

- Enrollment given demographics

$$1(12 < s_i < 16) = 1(\vec{\beta}_E \vec{X}_i + \varepsilon_E \geq 0)$$

- Continuation given demographics and grades

$$1(s_i \geq 16 | s_i > 12) = 1(\vec{\beta}_C \vec{X}_i + \beta_{C,g_m} 1(g = g_m) + \beta_{C,g_h} 1(g = g_h) + \varepsilon_C \geq 0)$$

External Spec

Financial Assistance by Demographics Estimate

Table 19: Funding by Demographic: External Estimate

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

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

Estimation Strategy

Finite Mixture Model Type Share-Selection

Table 20: Prob by Demographic: FMM

VARIABLES	Logit Uncond Prob High	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)
Observations	2,133	2,133	1,467

External Estimation

Finte Mixture Model Human Capital

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)
Observations	2,133	2,133	2,133	2,133
	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)	
Observations	2,133	2,133	2,133	

External Estimation

Finite Mixture Model Grades-Earnings

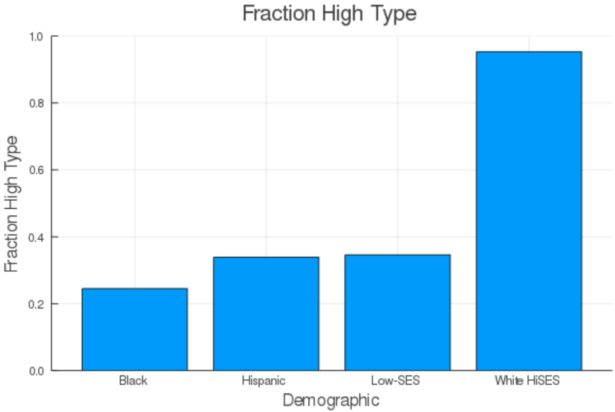
Table 22: Grades and Earnings: FMM

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)
Observations	1,467	1,467

	Linear log Avg Earnings
Intercept	9.879***
	(0.038)
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)
Observations	2,133

External Estimation

Fraction High Type



Estimation Strategy

Identification

Table 5: Key Internal Parameter Results

Parameter	Parameter Description	Target	Target Description
$\gamma_{p,0}$	Belief Constant	$\beta_{C,0}, \beta_{C,G_m}, \beta_{C,G_h}$	Constant, Coefficient med, high GPA on continuation
$\mu_c(\tau)$	Type dependent non pecuniary utility	$\beta_{C,0}, \beta_{C,G_m}, \beta_{C,G_h}$	Constant, Coefficient med, high GPA on continuation
$\gamma_{p,b}$	Belief: Meas Belief	$\beta_{E,B}$	Coefficient Meas Belief on enrollment
$\gamma_{p,h}$	Belief: 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

Targeted Moments: Indirect Inference Targets

Table 22: 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 NLSY Belief	0.215	0.201		
	(0.019)	(0.027)		
Funding T2	0.150	0.154	0.072	0.075
	(0.024)	(0.027)	(0.034)	(0.009)
Funding 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)

Targeted Moments

Results

Table: Key Internal Parameter Results

Table 23: Key Internal Parameter Results

Parameter	Description	Estimate
$\gamma_{p,0}$	Belief Constant	0.0057
		(0.0133)
$\gamma_{p,b}$	Belief: Meas Belief	0.88***
		(0.0103)
$\gamma_{p,h}$	Belief: P-Edu HSD	0.026**
		(0.0116)
$\gamma_{p,s}$	Belief: P-Edu SCOL	0.028***
		(0.0103)
$\gamma_{p,c}$	Belief: P-Edu Bach	0.055***
		(0.0102)
$\mu_{d,0}$	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)

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

Targeted Moments

Results: Average Earnings

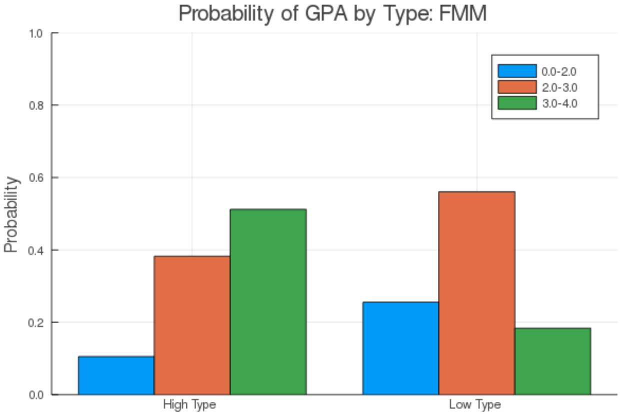
Table: External Estimation Results: Average Earnings

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 5: Expected value of earnings from Finite Mixture Model by education realization.

Estimation Strategy

Estimation Results



Estimation Strategy

Model Fit: Degree Attainment, Enrollment

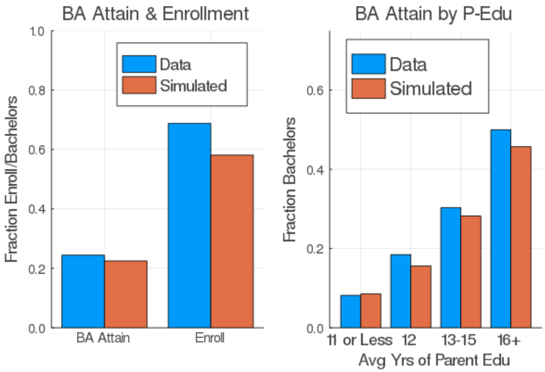


Figure: Fit of the Estimated Model: Enrollment, BA attainment, where Blue comes from the NLSY97 and Orange is simulated from the estimated quantitative model.

Model Estimate

Model Fit: Degree Attainment by Demographic Group

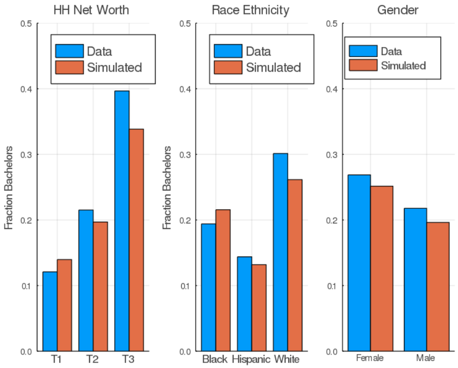


Figure: Fit of the Estimated Model: BA attainment by demographics, where Blue comes from the NLSY97 and Orange is simulated from the estimated quantitative model.

Model Estimate

Model Fit: Non Continuation by Grade

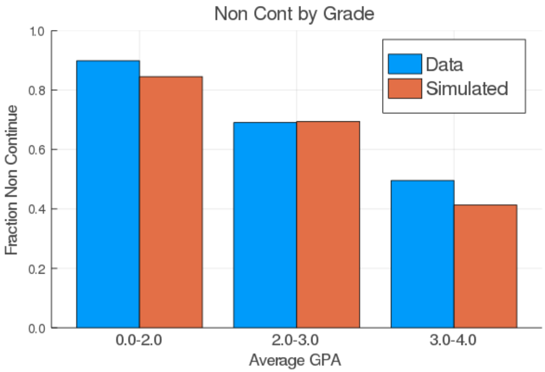


Figure: Fit of the Estimated Model: Non Continuation by GPA level, where Blue comes from the NLSY97 and Orange is simulated from the estimated quantitative model.

Model Estimate

Predicted Type Data vs Estimated Belief

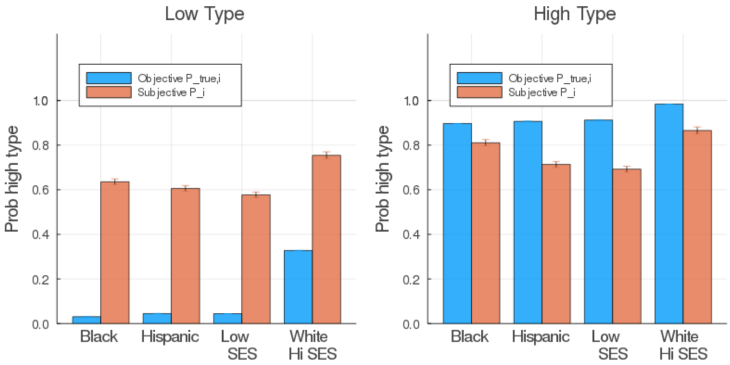


Figure: Compares the mean FMM estimate of prob high-scorer vs the mean subjective belief of being a high-scorer by scorer type.

Model Estimate

Mismatch by scorer type

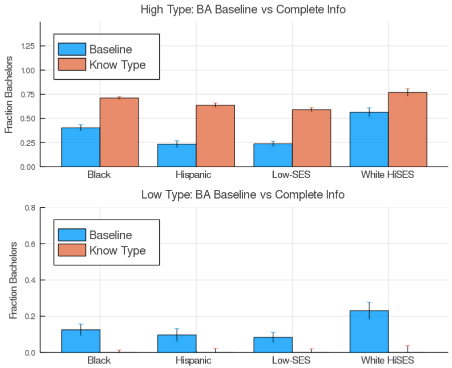
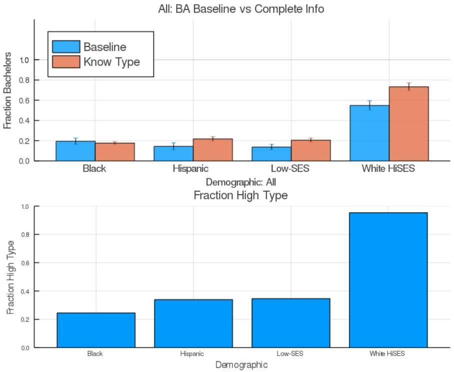


Figure: Shows difference in bachelor's attainment under baseline model and under scenario where youth know their true type with certainty.

Model Estimate

Mismatch Aggregate



Policy Effect

Difference in Causal Variables

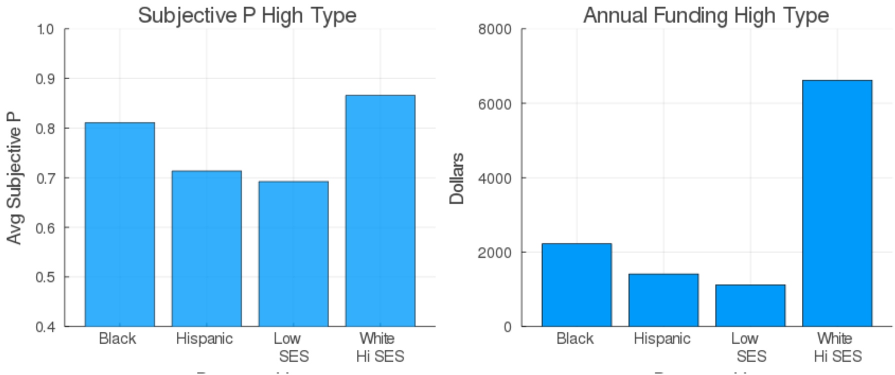


Figure: Estimated variables relating to causal mechanism by demographic group. Total financial assistance is the sum of family assistance and govt/college aid.

Model Estimate

Decomposition Continued

Table 8: Mechanism Decomposition: High Type

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

Decomposition Graph

Policy Effect on Inequality

Table 9: Policy Effect on Overall Inequality

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

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

Policy Effect