The Effects of Earnings Disclosure on College Enrollment Decisions

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Motivation

Large increase in rates of student loan default in the US in the 2000s

Driven by a small number of institutions/degree programs (Looney & Yannelis 2015)

- Default rates approaching 50% in some cases
- Mostly non-selective, for-profit providers
- Enrolling large shares of low-income students

One common policy approach: disclosure

- Idea: inform prospective students about outcomes
- Government collects data on costs, debt, earnings and passes to students
- Implemented in US, Australia, Colombia, Mexico, Peru (Neilson et al. 2016).

What we do

Disclosure is cheap and easy to implement, but benefits depend on:

- beliefs and preferences of applicants
- how helpful the information is

Use large scale policy experiment and survey in Chile to ask:

1. What are students who enroll in low-performing degrees thinking about earnings and costs?
2. How are enrollment choices affected by actual, scaled disclosure policy?
    - Student side: how does distribution of expected earnings change and why?
    - Institution side: which programs are most affected?

We also consider

3. Are earnings predictions reasonable guides to future outcomes?

Higher education in Chile

Market structure similar to US and other Latin American countries

- Public subsidy, private provision
- Similar to US in terms of tertiary share, subsidized loan share
- Important difference: apply to university-major combinations

Application timeline is as follows:

- November: fill out FAFSA equivalent ('FUAS') to apply for financial aid
- Early December: take admissions exam
- January: learn score, begin to apply
- March: new school year begins

Survey and intervention

Intervention we study here was part of the Fall 2012 application process

- Nested in financial aid app → access to *all* applicants (N=164,798)

Basic structure:

1. Students submit FUAS
2. Receive email from admissions authority
3. Asked to participate in brief survey, directed to link
   - at link, log in with ID number
   - fill out informed consent
4. Take survey
5. Split off into treatment and control arms at random (N=49,166)

Intervention strongly resembles US College Scorecard (2015) More

Measuring earnings and costs

Use earnings and cost data to *treat*, *benchmark*, and *evaluate*

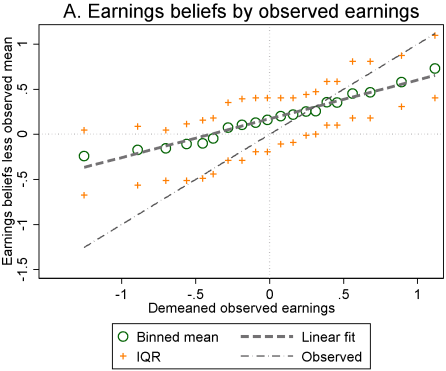
- population tax data (2005-2012)
- administrative education records (1990s and ff)

1. Costs
   - Ask about total cost of attending degree for a year
   - Benchmark to 'sticker price' from admin data
   - Treat w/ monthly payment associated with paying back sticker price over 15 year repayment period
2. Earnings
   - Ask about earnings for *graduates* once they leave college and begin work
   - Benchmark to earnings for *graduates* one to two years post-completion
   - Treat w/ monthly earnings for graduates over first 15 years of career
     - Good: easy for students to understand, gov't likes, data available
     - Bad: not everyone graduates
   - When evaluating effects of treatment, look at multiple measures
     - Earnings for graduates
     - Regression-adjusted earnings for enrollees at age 26

More

Earnings beliefs for typical graduates

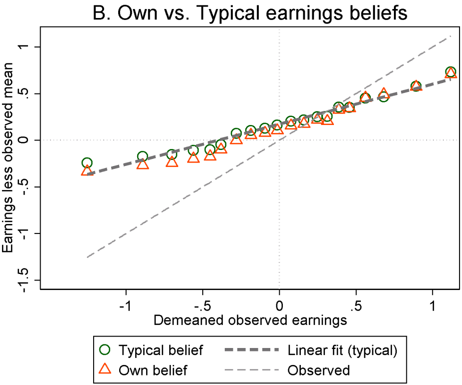
Applicants overestimate at bottom, underestimate at the top



- First evidence on beliefs for students at worst programs
- Consistent w/ ∼ accurate expectations at top (Wiswall & Zafar 2014)
- Similar slope *within* person ▸ More

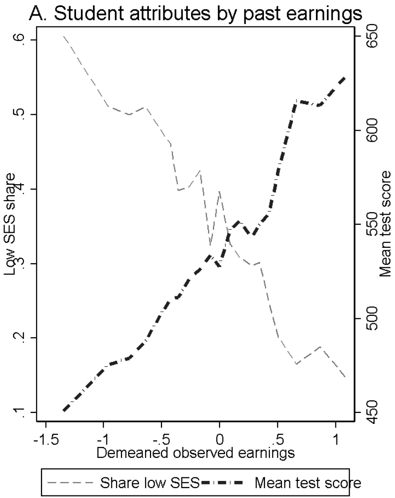
Own earnings vs. typical graduate earnings

People think own earnings $\sim$ typical earnings



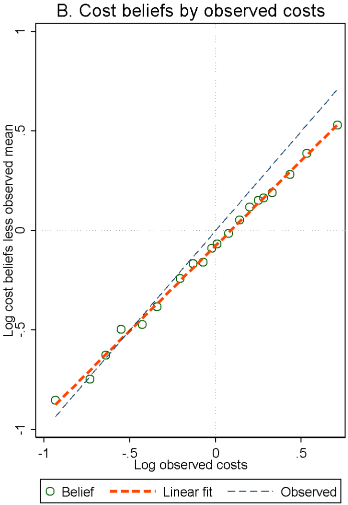
- Correlation between beliefs about own vs. 'typical graduate' earnings: 0.80

Low-SES, low-scoring students choose low-earning degrees



Cost beliefs

Accurate on average across the distribution



Elicited preferences and beliefs predict behavior

Preferences predict behavior

- 45% enroll in one of listed preferences
- 27% in first choice
- 57% in first choice conditional on having a qualifying score
- Can condition on enrollment and get similar belief distribution ▸ More

Beliefs predict preferences

- Beliefs about own earnings predict preference rankings;
- Conditional on beliefs, observed earnings values do not ▸ More
  → Earnings concept we ask about is meaningful to students
- Survey findings unaffected by different benchmarking approaches ▸ 1 ▸ 2
  → Errors do not seem to reflect misevaluation of 'accurate' beliefs

Modeling beliefs

Linear form w/ slope less than one consistent with simple Bayesian model

- Applicants have some belief about return to college on average
- Some noisy signal about earnings at specific degrees
- $\rightarrow$ 'Shrink' back to prior belief about overall mean
- Slope of line α_Y maps to noise-to-signal ratio: $\frac{1-\alpha_Y}{\alpha_Y} = \frac{\sigma_e^2}{\sigma_Y^2}$
  - Earnings: $\frac{\sigma_e^2}{\sigma_Y^2} = 1.34$
  - Costs: $\frac{\sigma_e^2}{\sigma_Y^2} = 0.14$

Implications:

- Low-quality benefit from mean-zero uncertainty (Johnson & Myatt 2006)
- Suggests role for learning, esp. on earnings side.
- Consistent w/ limited effect for costs (Bettinger et al. 2012; Hoxby & Turner 2013)

More

Experimental approach

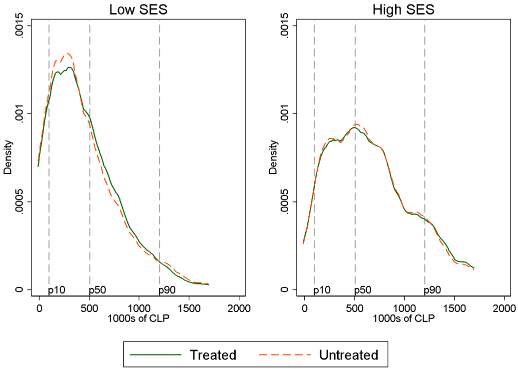
Test these predictions using experimental intervention.

We estimate equations of the form

$$Y_i^{outcome} = \beta_0 + \beta_1 T_i + \beta_2 X_i + \gamma_{g(i)} + e_i \tag{1}$$

- $Y_i^{outcome}$: some-post-treatment outcome
  - Do you matriculate?
  - Earnings/costs for graduates of degree where you matriculate
  - Earnings/costs for *enrolling* students where you matriculate
- T_i: treatment dummy
- X_i: individual covariates
  - Key covariate: attributes of your stated first choice degree program
- $\gamma_{g(i)}$: randomization block fixed effects (groups of schools)

Figure: Distribution of earnings predictions by treatment status



Experimental effects conditional on matriculation:

- Bottom tercile share ↓ 3.3% overall, 4.6% for low-SES

Experimental estimates

Table: Impact of treatment on outcome variables

	Pooled	Low-SES	High-SES	Low-PSU	High-PSU	Low SES & PSU
Matriculation	0.004	0.000	0.003	-0.005	0.008	-0.012
	(0.004)	(0.008)	(0.006)	(0.006)	(0.005)	(0.010)
Conditional on Matriculation (CLP)						
A. For graduates						
Mean earnings	10,971*	16,083*	9,066	13,091*	8,438	19,288*
	(4,532)	(7,671)	(5,819)	(5,887)	(5,784)	(7,795)
Monthly Debt	376	763	125	1,036*	-166	750
	(435)	(680)	(580)	(491)	(552)	(610)
Net Value	10,029*	15,274*	8,040	12,008*	7,545	18,430*
	(4,230)	(7,149)	(5,435)	(5,547)	(5,455)	(7,366)
B. For enrollees						
Earnings prediction	6,324*	11,759**	3,789	2,682	7,936*	11,337**
	(2,814)	(4,425)	(3,771)	(3,421)	(3,949)	(4,396)
Monthly Payment	498	824	344	1,197*	164	933
	(459)	(758)	(568)	(578)	(546)	(713)

Table: Impact of treatment on outcome variables

Augmenting experiment w/ model

Descriptive and experimental findings:

- Beliefs are inaccurate
- Disclosure $\rightarrow$ higher-earning programs
- But lots of people don't switch

Would like to understand

- Mechanisms that mediate treatment effects $\rightarrow$ policy design
- Distributional effects across institutions $\rightarrow$ Δ incentives

Augmenting experiment w/ model

Combine w/ choice model to get at this

- Builds on belief updating framework $\rightarrow$ treatment increases precision of signal
- Applicants maximize utility from available options:

$$\max_{j \in J_i} u_{ij} = X_j \beta_1 + X_{ij} \beta_2 + \pi_0^Y \tilde{Y}_j + \pi_1^Y \tilde{Y}_j T_i + \pi_0^C \tilde{C}_j + \pi_1^C \tilde{C}_j T_i + \epsilon_{ij} \quad (2)$$

  - J_i: choice set defined by test scores (Conlon & Mortimer 2013; Bucarey 2017)
  - X_j, X_{ij}: degree attributes+interactions w/ i's characteristics
  - $\tilde{Y}_j$, $\tilde{C}_j$: true values of typical earnings and costs
  - T_i: treatment indicator

Need to assume that:

- We have right choice set, and applicants know choice set
- Applicants choose most-preferred feasible degree

Payoff:

- Rich substitution patterns using elicited preferences, not random effects
- In updating model: $(\pi_1^Y - \pi_0^Y)/\pi_0^Y = (\alpha_Y(1) - \alpha_Y(0))/\alpha_Y(0)$

Mechanisms

People learn from treatment but don't care that much about earnings

Table: Utility weights and enrollment elasticities for earnings and costs

	All	Low SES	High SES
A. Utility weights			
Earnings			
Treated	0.3666	0.4844	0.3513
Untreated	0.2879	0.2977	0.3159
Share $\Delta \frac{\sigma_e^2}{\sigma_Y^2}$	-0.43	-0.71	-0.25
Costs			
Treated	-0.6197	-1.2305	-0.2334
Untreated	-0.6042	-1.1262	-0.2416

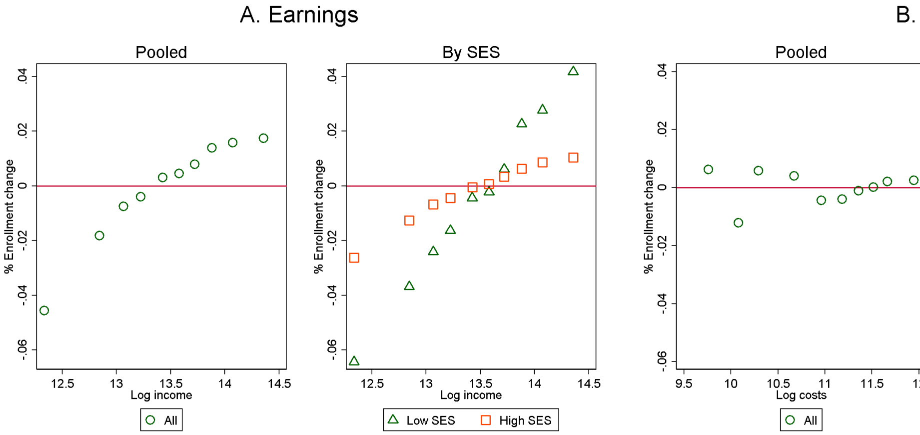
Table: Utility weights and enrollment elasticities for earnings and costs

	All	Low SES	High SES
A. Utility weights			
Earnings			
Treated	**0.3666**	**0.4844**	**0.3513**

Distribution across institutions

Treatment reduces enrollment most at lowest earning institutions

Figure: Enrollment effects by decile of attribute



- People move *between* non-selective degrees w/ slack capacity

Questions you may have

About the model:

- Does intervention operate by making certain degrees more salient? More
  - Not just telling people what to do or informing about choice set
  - Place more weight on earnings in general
- Are results robust to alternate formulations of the choice set?
  - Alternate analysis focusing on listed preferences $\rightarrow$ yes

About the experiment/policy:

- What happens to treated people over medium run? More
- Do gains in 'predicted' earnings translate to long-run gains?

Long-run impacts of treatment

Final question: do earnings predictions map to long-run gains?

- Test by comparing earnings predictions to causal estimates from RD design
- Similar in spirit to Kane & Staiger (2008), Chetty et al. (2014a, 2014b), Deming (2014)
- RD based on cutoff rules at selective programs (HNZ 2013)

Approach:

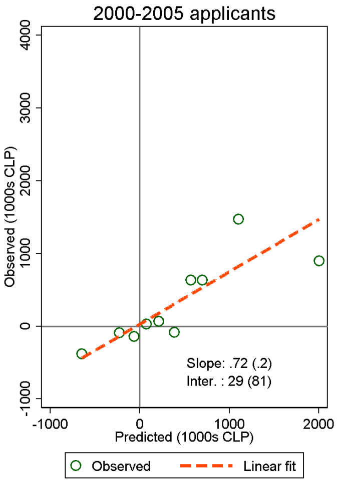
- Look at admissions cutoff for several hundred degree programs
- Compute RD estimates of earnings changes at each cutoff
- Recompute RD estimates using earnings *predictions*
- Estimate specifications of the form

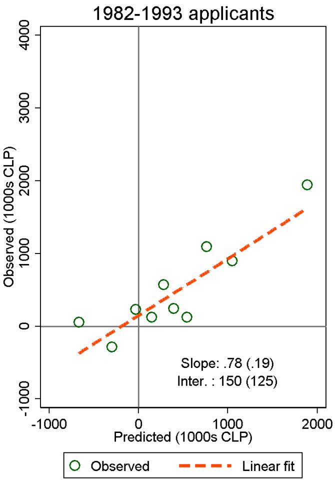
$$\hat{\delta}_j^{obs} = \lambda_0 + \lambda_1 \hat{\delta}_j^{pred} + e_j \tag{3}$$

- Prediction: after accounting for measurment error, $\lambda_0 = 0$ and $\lambda_1 = 1$.

Benchmarking exercise

Figure: Observed and predicted cross-threshold earnings changes





Summary and policy implications

We use actual change in policy at scale to show that

- Students enrolling in low-earning programs overestimate earnings outcomes
- Disclosure of earnings outcomes reduces enrollment in these programs
- Students learn, but effects are limited by strong preferences for non-pecuniary attributes
- Worth it from a cost-benefit perspective

Policy points:

- Details matter– pilot w/o government contacts had extremely low takeup
  - Important to study *policy* (Muralidharan & Niehaus 2017)
- Disclosure effects may grow over time...
  - supply response
  - students learn to think about earnings as more important component of choice
- ... but regulation may be necessary if you want to limit low quality market share in short run

Our intervention vs. College Scorecard

Proyecto 3E

Expectativas. Estudiantes. Educación.

Las remuneraciones de los titulados son un factor que muchos estudiantes consideran cuando están pensando en qué carrera y dónde estudiar, aunque el sueldo es solamente un aspecto a tomar en cuenta en una decisión bien informada. Hay varios otros factores que pueden afectar tu grado de satisfacción con tu carrera en el futuro, tales como el costo de los estudios, los beneficios personales que puedes recibir, y por supuesto, tu vocación y tus preferencias. Todos estos son factores importantes al momento de elegir una carrera y una institución de educación superior.

Considerada información histórica proyectada respecto a las remuneraciones y el costo total de las carreras, ésta podría ser tu situación de ingresos futuros:

Institución	Carrera	Aumento en ingresos mensuales en comparación al sueldo de aquellos sin un título de educación superior* A	Costo total de la carrera, en pagos mensuales* B	Valor Neto Mensual Esperado o (A-B)
UNIVERSIDAD LA REPUBLICA	Ingeniería en Medio Ambiente	$1.520.000	$430.600	$1.089.400
UNIVERSIDAD DEL MAR	Ingeniería en Medio Ambiente	$1.258.000	$515.667	$742.333

Aumento en ingresos mensuales en comparación al sueldo de aquellos sin un título de educación superior, es el aumento en ingresos proyectado para titulados de generaciones anteriores de esa institución y carrera, en comparación con los ingresos proyectados para personas sin un título de educación superior.

Earnings predictions

We compute two sets of earnings predictions

1. Earnings and 'net value' conditional on graduation

$$NV_j = \sum_{t=1}^{t=15} \beta^t (\hat{\mu}_{jt} - \hat{\mu}_{0t}) - C_j \tag{4}$$

   - $\hat{\mu}_{jt}$: mean earnings for graduates of j in year t after graduation
   - $\hat{\mu}_{0t}$: mean earnings for students who do not go to college
   - C_j: total cost of attending j.

2. Regression adjusted earnings conditional on enrollment

$$\begin{aligned} y_{ijct} &= X_{ict}\beta_{s(j)} + W_{ijct}\delta_{m(j)s(j)} + v_{ijct} \\ v_{ijct} &= \mu_{jc} + \epsilon_{ijct} \end{aligned} \tag{5}$$

   - y_{ijct}: earnings for students i enrolling in j in cohort c in year t.
   - X_{ict}, W_{ijct}: student covariates and interactions w/ degree characteristics
   - μ_{jc}: degree-cohort specific mean residual

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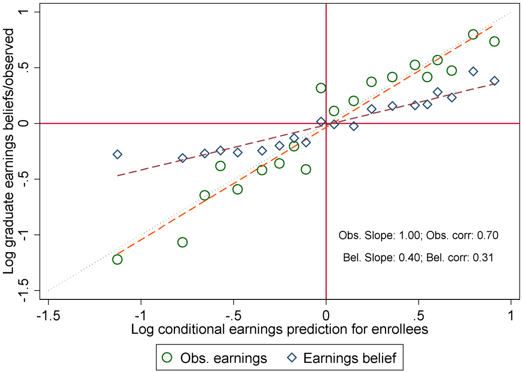
Earnings predictions

Figure: Observed and expected earnings for graduates by VA prediction for enrollees



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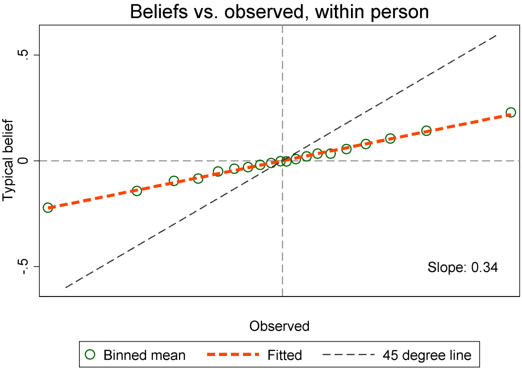
Within-person slope of beliefs in observed values



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Earnings beliefs, observed values, and preference rankings

Table: Exploded Logits

	1	2	3
Observed earnings	0.1158**		0.0630
	(0.0347)		(0.0450)
Observed costs	-0.4992**		-0.6187**
	(0.0494)		(0.0675)
Earnings beliefs		0.3260**	0.3543**
		(0.0453)	(0.0467)
Cost beliefs		-0.0823*	0.0478
		(0.0373)	(0.0407)
N	57740	42558	42483

Coefficient estimates from exploded logits. Sample: students' elicited preferences (up to three per student). Dependent variable is listed rank. "Observed earnings" and "Observed Costs" are authors' calculations of observed values for past graduates. "Earnings beliefs" and "Cost beliefs" are students' reported own-earnings and own-cost beliefs from survey data. Standard errors cluster at student level.

Earnings beliefs

Modeling beliefs

Linear form w/ slope less than one consistent with simple Bayesian model:

- Applicants believe past earnings $\tilde{Y}_j$ have distribution $N(\bar{Y}+b, \sigma_Y^2)$
  - $\bar{Y}$ =true mean, b =belief bias
- Individuals i receive noisy signal about past earnings at j, $\tilde{Y}_{ij} = \tilde{Y}_j + b + e_{ij}$
  - $e_{ij} \sim N(0, \sigma_e^2)$
- Bayesian updating means posterior beliefs about earnings at j given by

$$\tilde{Y}_{ij}^e = b + \alpha_Y \tilde{Y}_j + (1-\alpha_Y)\bar{Y} + r_{ij} \tag{6}$$

- $\alpha_Y = \frac{\sigma_e^{-2}}{\sigma_e^{-2}+\sigma_Y^{-2}}$ is precision weighting

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Earnings beliefs

Modeling beliefs

$$\tilde{Y}^e_{ij} = b + \alpha_Y \tilde{Y}_j + (1 - \alpha_Y)\bar{Y} + r_{ij}$$

Three points:

1. Predictions differ from alternate models, e.g. systematic upward bias, misleading advertising
2. Model predicts that bad programs benefit from mean-zero uncertainty $\rightarrow$ 'shrunk' back towards overall mean
3. Can recover quantitative estimates of bias term b and noise-to-signal ratio $\frac{\sigma_e^2}{\sigma_Y^2} = \frac{1-\alpha_Y}{\alpha_Y}$ from graph
   - $\alpha_Y \sim 0.427 \rightarrow \frac{\sigma_e^2}{\sigma_Y^2} = 1.34$
   - b=0.17

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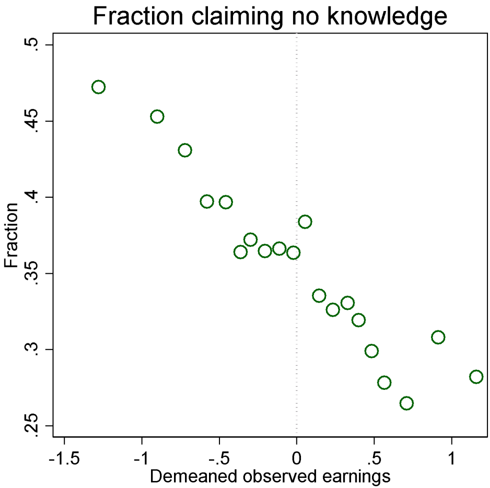
Earnings nonresponse



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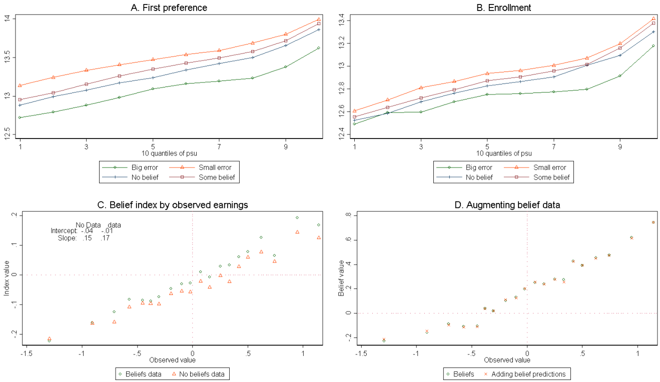
Earnings nonresponse

Figure: Assessing belief nonreports



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Sampling error and slope of beliefs in observed values

Table: Measurement error in observed earnings values

	Logs	Levels
Statistics		
Obs per. Degree	491	491
Effect SD σ_μ	0.590	459
Sampling SD $\sigma_{\bar{\epsilon}}$	0.066	53
Slopes		
Uncorrected	0.427	0.421
	(0.005)	(0.008)
Corrected	0.437	0.439
	(0.005)	(0.008)

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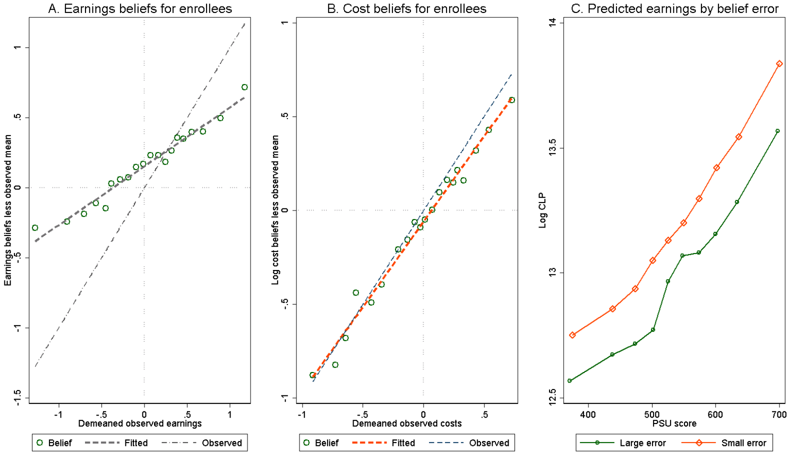
People follow through on enrollment plans

Figure: Beliefs for enrollees



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Information treatment and program-specific demand

Ignoring cost preferences for convenience, rewrite choice problem as

$$\max_{j \in J_i} u_{ij} = X_j \beta_1 + X_{ij} \beta_2 + \tau_Y \mathbf{Y^e_{ij}} + \tilde{\varepsilon}_{ij}$$

- Treatment changes expectations by raising belief precision α_Y
- Define $\alpha_y(t)$ as precision of earnings beliefs for $T_i = t$
- Then can show that

$$(\pi^Y_1 - \pi^Y_0)/\pi^Y_0 = (\alpha_Y(1) - \alpha_Y(0))/\alpha_Y(0)$$

$\rightarrow$ can measure effect of treatment precision of signal using % effect of treatment on weight placed on observed earings

$\rightarrow$ Overall effect of observed earnings on choice is scaled by own earnings preference and relevance of past earnings for own outcomes

Updating vs. recommendation salience

Table: Selected logit coefficient estimates

	All	Low SES	High SES	All	Low SES	High SES
Treat × earn	0.0897+	0.187*	0.0354	0.0875	0.185*	0.0332
	(0.054)	(0.088)	(0.068)	(0.054)	(0.088)	(0.068)
Treat × cost	-0.0315	-0.104	0.00826	-0.0324	-0.107	0.00801
	(0.049)	(0.078)	(0.064)	(0.049)	(0.079)	(0.064)
Treat × rec'd				0.124	0.191	0.0911
				(0.155)	(0.264)	(0.192)
N	13112133	4518344	8593789	13112133	4518344	8593789

Selected coefficient estimates from logit estimation. Observations are at student-option level for degree programs in each student's choice set. Columns define student sub-samples. +: $p < 0.10$, *: $p < 0.05$, **: $p < 0.01$ **: $p < 0.001$.

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How do people substitute?

Table: Utility weights and enrollment elasticities for earnings and costs

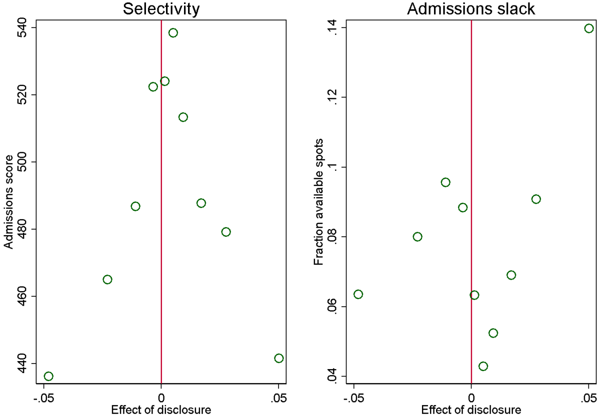
	All	Low SES	High SES
B. Earnings elasticities at first choice program			
Baseline			
Treated	0.1816	0.2378	0.1748
Untreated	0.1428	0.1462	0.1574
No geography			
Treated	0.2104	0.2842	0.1994
Untreated	0.1655	0.1748	0.1795
No institutional			
Treated	0.2943	0.3909	0.2809
Untreated	0.2312	0.2403	0.2527
No major			
Treated	0.3206	0.4216	0.3081
Untreated	0.2519	0.2593	0.2772

Table: Utility weights and enrollment elasticities for earnings and costs

What about crowdout?

People move *between* non-selective degrees

Figure: Selectivity and admissions slack by enrollment change



People switch *between* non-selective programs; low earnings → higher earnings.

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Treatment and dropout/switching

Table: Disclosure and persistence in degree programs

	Pooled	Low SES	High SES
A. Sample means			
Matriculate anywhere 2014	0.873	0.804	0.926
Dropout 2014	0.084	0.124	0.051
Change degree 2013 vs. 2014	0.155	0.154	0.15
Change institution 2013 vs. 2014	0.095	0.089	0.093
Change major 2013 vs. 2014	0.139	0.138	0.135
B. Treatment effects			
Characteristics of chosen degree			
Degree graduation rate	0.002	0.002	0.002
	(0.003)	(0.005)	(0.004)
Degree length	0.014	0.019	0.01
	(0.018)	(0.032)	(0.023)
Persistence into second year			
Matriculate anywhere 2014	-0.002	0.002	-0.006+
	(0.003)	(0.007)	(0.003)
Dropout 2014	0.003	0.002	0.003
	(0.003)	(0.007)	(0.003)
Change degree 2013 vs. 2014	-0.002	-0.003	-0.002
	(0.004)	(0.008)	(0.005)
Change institution 2013 vs. 2014	0.001	0.000	0.002
	(0.003)	(0.006)	(0.004)
Change major 2013 vs. 2014	-0.002	-0.003	-0.003
	(0.004)	(0.007)	(0.005)

Panel A: Means of 2014 matriculation outcomes by SES.Panel B: effects of disclosure treatment on listed outcome. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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