Funding Instruments and Effort Choices in Higher Education

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Introduction

INTRODUCTION

- Multiple funding instruments are in place in Higher Education (means, merit-based loans, scholarships).
- Tuition-Free Higher Education (TFHE) has been in the public debate in several countries (Community College in the US, Colombia, Chile).
    - Equity vs. Efficiency
        - Subsidizing tuition facilitates access and human capital accumulation.
        - Reduces financial frictions, but affects incentives to exert effort and sort efficiently across education levels and institutions. Performance requirements?
    - Regressive concerns
        - Higher-income students are more likely to attend and complete college.
- **How to target financial aid?**

- **What is the impact of Tuition-Free Higher Education (TFHE)?**
  - We estimate the effect of TFHE for the first five income deciles in Chile in 2016 using Difference-in-Differences.
    - Enrollment rose by 5p.p. in 2016 and 15p.p. in 2017 for eligible students. Driven by low-ability.
    - Dropout decreases by 2 p.p. for infra-marginal students and on-time graduation rises.

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How to better target financial aid?

- TFHE lowers entry barriers and alleviates financial stress allowing students to focus more on coursework.
- But it can also attract students who enjoy the "college experience" but have high effort costs.
- We build a structural model of enrollment and credit completion with endogenous (unobserved) effort.
  - Allows us to **separate marginal from infra-marginal** students and recover the full distribution of TE.
  - Identifies marginal cost of effort and predicts **effort responses in counterfactual funding schemes**.

CONTRIBUTION

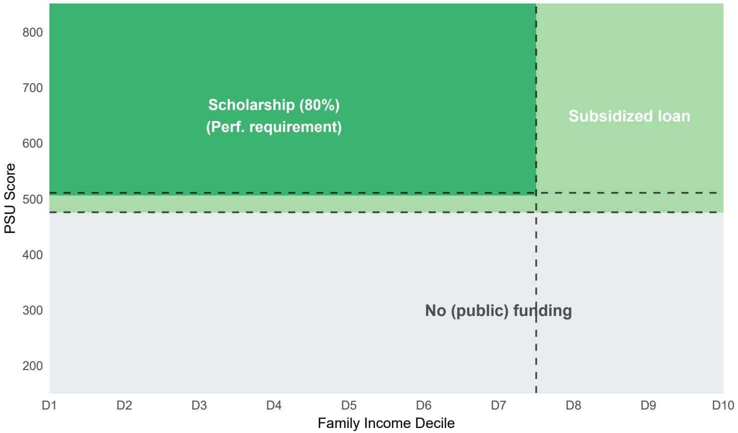
- Impact of financial aid on higher education
  - Effects on enrollment: Angrist et al. (2015) and Denning (2017) find a positive effect for the US, Solis (2017) for Chile.
  - Mixed results and less evidence on educational outcomes: Dynarski (2003), Cohodes and Goodman (2014), Denning (2019) for the US, Fack and Grenet (2015) for France, Solis (2025) for Chile.
    $\hookrightarrow$ **we evaluate the impact of a large-scale free college policy in a context where both means- and merit-based aid coexist.**
- Dynamic modeling of educational policies
  - Effort and academic outcomes: effort in high school and subjective beliefs (Tincani et al., 2023); on school track choices (De Groote, 2025). College admission probabilities (Arcidiacono, 2005), length of studies (Beffy et al., 2012).
  - Financial aid: loans vs credits (Joensen and Mattana, 2024), Ferreyra et al. (2022).
    $\hookrightarrow$ **we endogenize (unobserved) effort under alternative funding schemes.**

Context

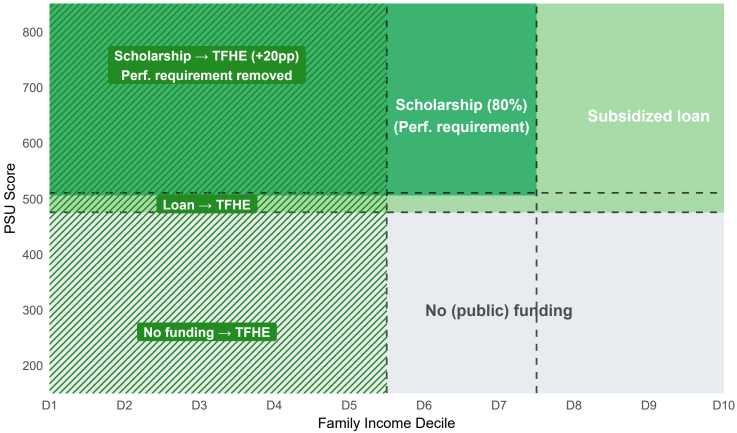
INSTITUTIONAL BACKGROUND: CHILE

- Access higher education after taking national exam (PSU).
- Tuition is among the highest in OECD countries. Annual tuition is roughly half the median annual wage. Funding options (2015):
  - subsidized loans: score above 475 PSU.
  - scholarships: score above 510 PSU, belong to the lowest 7-8 deciles of the income distribution.
    - Cover 80% of tuition.
    - Performance requirement: **pass 70% of yearly credits** to maintain it.

PRE-POLICY SETTING

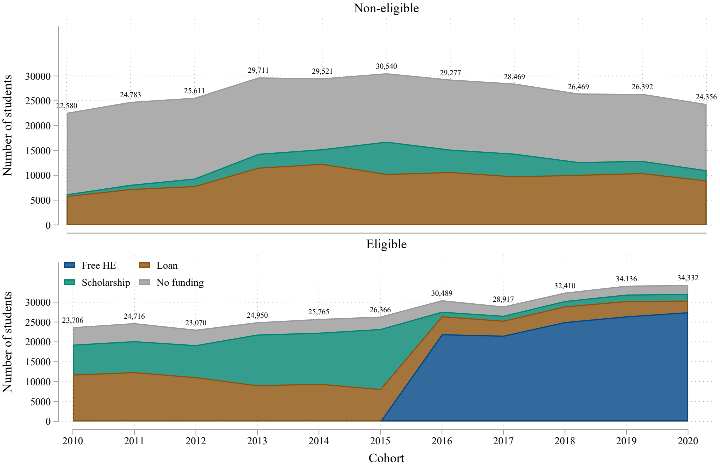


FREE HE: GRATUIDAD (2016)



Policy changes in funding instruments.

FREE HE: GRATUIDAD (2016)



Changes in funding sources over cohorts.

Decile

SUBSTITUTION OF FUNDING

Affected relatively low-income students very differently.

- High-ability $\rightarrow$ switched from merit scholarship ($>$ 510 PSU) covering 80% to 100% (and performance requirement removed).
- Mid-ability $\rightarrow$ switched from subsidized loan ($>$ 475 PSU) to TFHE.
- Low-ability $\rightarrow$ switched from no (public) funding to TFHE.

DATA AND SAMPLE

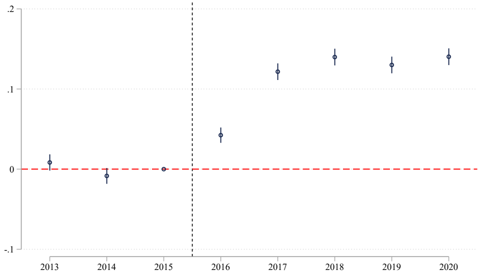
- Chilean administrative records
  - Universe of students that took the national entry exam (score, demographics, enrollment).
  - College students' records, scholarship applications and awards.
  - Yearly credits registered and completed (starting 2016). Credits
- Survey data: wage and employment by field of study.
- Sample: first-time test takers.
  - Cohorts 2010 to 2017 (degrees last 5 years in Chile).
  - Around 180,000 students annually.

Desc

Quasi-Experimental Evidence

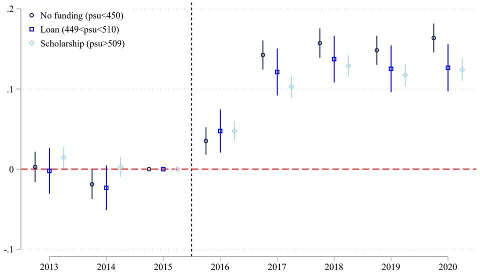
DID: ENROLLMENT

$$Y_{it} = \sum_{\substack{k=2013 \\ k\neq 2015}}^{2020} \beta_k \left(\mathbf{1}\{t=k\} \times \mathbf{1}\{dec_i < 6\}\right) + \gamma\, \mathbf{1}\{dec_i < 6\} + \delta_{\mathbf{t}} + \mathbf{X}_{\mathbf{i}}'\alpha_{\mathbf{x}} + \epsilon_{\mathbf{it}}$$



Notes. OLS coefficient estimates (and their 95% confidence intervals) are reported.
2015 Mean of dep. variable: 0.62.

a) Effect on enrollment



Notes. OLS coefficient estimates (and their 95% confidence intervals) are reported.
2015 Mean of dep. variables: 0.48, 0.60 and 0.77, respectively.

b) Effect on enrollment by funding eligibility

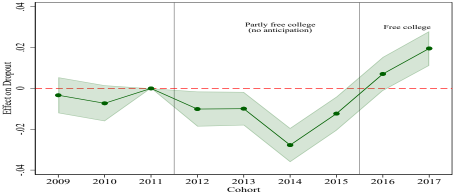
More

DID: EDUCATIONAL OUTCOMES

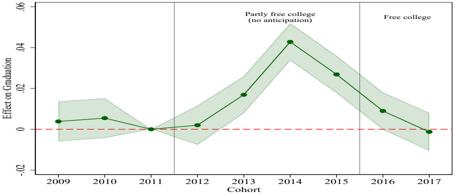
- Educational outcomes are difficult to measure after the policy if it induced selection.
  - But cohorts before 2016 were also eligible for the remaining years of the program.
  - 2012 cohort could potentially benefit from 1 year of the policy, 2 years for the 2013 cohort, etc.
  - Cohorts prior to 2016 do not suffer from selection bias since their enrollment decisions had already been made.

$$Y_{it} = \sum_{\substack{k=2010 \\ k \neq 2011}}^{2017} \beta_k^c \left(\mathbf{1}\{t = k\} \times \mathbf{1}\{dec_i < 6\}\right) + \gamma^c \, \mathbf{1}\{dec_i < 6\} + \delta_t^c + \mathbf{X_i}'\boldsymbol{\alpha}_x^c + \epsilon_{it}^c$$

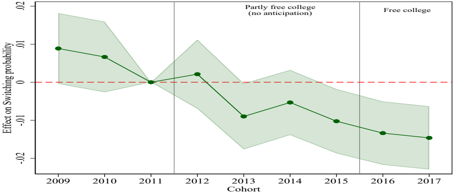
DID: EDUCATIONAL OUTCOMES



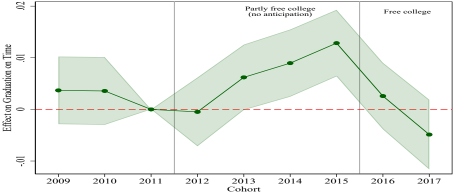
a) Dropout



b) Graduation



c) Field switching



d) Graduation on Time

TAKEAWAYS

- Quasi-experimental evidence suggests a substantial increase in enrollment for *eligible* students, driven by low-ability students. Composition
  - Estimate could be magnified by spillover effects.
- Educational outcomes improve only for *infra-marginal* students.
  - Dropout falls by 2 p.p. for infra-marginal students, on-time graduation rises.
  - Null effects on graduation for cohorts starting 2016.

Empirical model

OVERVIEW OF THE MODEL

State Variables ($x_{i,t}$)

- t
- $OP_{i,j,t}$: out-of-pocket fees
- $d_{i,t-1}$: program
- $g_{i,t-1}$: last period performance
- $G_{i,t-1}$: cumulative credits
- Z_i : individual characteristics

Choice Variables

- Period 1: program $d_{i1} = j \in \mathcal{J}_i$
- Each t: effort $e_{it} \in (0, \infty)$
- $t \geq 2$: continue $d_{it} = d_{it-1}$ or drop out $d_{it} = 0$

Timing

1. **Entry:** Observe funding instruments, choose program and effort.
2. **Continuation:** Periods $t = 2, \ldots, 7$
   - Observe performance $g_{i,t-1}$ (credit realization).
   - Decide to continue $d_{i,t} = d_{i,t-1}$ or drop out $d_{i,t} = 0$.
   - Choose effort $e_{i,t}$.
3. **Terminal:** At $t = 7$, if not graduated $\Rightarrow$ drop out, enter labor market.

FLOW UTILITY

We interpret utility as a cost of attending higher education (De Groote, 2025).

$$u_j(x_{i,t}) + \varepsilon_{ijt} = -\underbrace{FC_j(x_{i,t})}_{\text{fixed cost}} - \underbrace{c_j(x_{i,t})e_{i,t}}_{\text{variable cost}} + \varepsilon_{ijt}$$

with $\varepsilon_{ijt} \sim EV1$, $c_j(x_{i,t})$ marginal cost, and $e_{i,t}$ *effective* effort. Out-of-pocket fees are given by

$$OP(Z_{i,}, g_{i,t-1}, P_{j,t}) = \begin{cases} (1-\lambda(Z_i, g_{i,t-1}))P_{j,t} & \text{if the student holds a scholarship,} \\ (1-\lambda(Z_i))P_{j,t} & \text{otherwise .} \end{cases}$$

where λ is the fraction of the fees subsidized by the Government, $g_{i,t-1}$ is last year credit performance, and $P_{j,t}$ is the degree price.

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Starting in 2016 $\rightarrow$ $OP(Z_i, g_{i,t-1}, P_{j,t}) = OP_j(Z_i) = 0$ for students eligible to TFHE.

FC

EFFORT, CREDIT COMPLETION AND GRADUATION

- Effort has an impact on performance outcomes. By exerting more effort, the student **increases her probability of passing credits** $g_{i,t}$.

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$$g_{i,t+1} = \kappa \text{ if } \bar{g}^{\kappa} < \ln e_{i,t} + \eta_{i,t+1} \leq \bar{g}^{\kappa+1}$$

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$$e_{i,t} = \frac{1 - \Pr(g_{i,t+1} = 0 | x_{i,t}, d_{i,t})}{\Pr(g_{i,t+1} = 0 | x_{i,t}, d_{i,t})}$$

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- **Graduation** occurs when the cumulative number of credits equals the amount required by the program.

MARGINAL COST OF EFFORT

$$v_j(x_{it}, e_{it}) + \varepsilon_{ijt} = u_j(x_{it}, e_{it}) + \beta \sum_{\bar{g} \in \mathcal{G}} \phi^{\bar{g}}(e_{it}) \bar{V}(x_{it+1}(\bar{g})) + \varepsilon_{ijt}$$

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where $\phi^{\bar{g}}(e_{it})$ is the probability to obtain credits $\bar{g}$. Taking the FOC wrt. effort,

$$\frac{\partial v_j(x_{it}, e_{it})}{\partial e_{it}} = \underbrace{\frac{\partial u_j(x_{it}, e_{it})}{\partial e_{it}}}_{=-c(x_{it})} + \beta \sum_{\bar{g} \in \mathcal{G}} \frac{\partial \phi^{\bar{g}}(e_{it})}{\partial e_{it}} \bar{V}(x_{it+1}(\bar{g})) = 0 \text{ if } e_{it} = e^*_{it}(x_{it})$$

$$c_j(x_{it}) = \beta \sum_{\bar{g}} \frac{\partial \phi^{\bar{g}}_{ijt}(e_{it})}{\partial e_{it}} \bar{V}(x_{it+1}(\bar{g})) \text{ if } e_{it} = e^*_{it}$$

Student chooses j with higher $v_j + \varepsilon_{ijt}$ after solving for optimal effort in each program.

Estimation

ESTIMATION

Given the Type-1 extreme value assumption, CCPs are of logit type. Following Hotz and Miller (1993), and using dropout ($j = 0$) as an arbitrary choice,

$$v_j(x_{it}, e_{it}) + \varepsilon_{ijt} = u_j(x_{it}, e_{it}) + \beta \sum_{\bar{g} \in \mathcal{G}} \phi^{\bar{g}}(e_{it})(\alpha_w wage_0(x_{it+1}) - \ln p_0(x_{it+1}(\bar{g}))) + \beta\gamma + \varepsilon_{ijt}$$

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3. Finally, we use the estimates and the FOC to compute $c(x_{it})$.

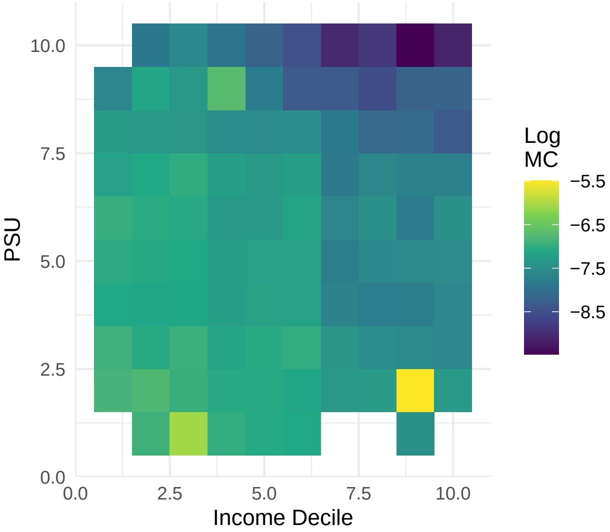
Results

FIXED COSTS

	Fixed Costs	
OP fees	0.950***	(0.039)
Distance	0.285***	(0.039)
Delay (t-1)	-0.251***	(0.080)
Rel. Ability	-0.191***	(0.043)
OP x female	0.232***	(0.036)
OP x middle SES	-0.004	(0.042)
OP x high SES	0.082*	(0.048)
OP x psu	0.079***	(0.023)
OP x gpa	0.043**	(0.022)
Delay (t-1) x female	0.089	(0.088)
Delay (t-1) x middle SES	0.511***	(0.102)
Delay (t-1) x high SES	1.199***	(0.123)
Delay (t-1) x psu	-0.680***	(0.050)
Delay (t-1) x gpa	0.215***	(0.054)
EMAX	0.950	(.)
Expected wage	2.914***	(0.126)
Field FE	Yes	
Institution FE	Yes	

Standard errors in parentheses
Conditional Value function Estimation
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

MARGINAL COSTS



Next steps

COUNTERFACTUALS

- Treatment effects (net of selection)
  - Recover the distribution of treatment effects along observed heterogeneity.
  - Identify students who switch from $d_{it} = 0$ to $d_{it} = j$ *because* of TFHE from students that would have enrolled anyway.
  - Validate using the reduced-form results.

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- Optimal Policy
  - Adjust merit and performance requirements as for scholarships.
  - Vary the subsidy amount.
- Major choice
  - Tuition impacts the fixed cost of higher education. Does TFHE make students choose differently? (De Falco and Reichlin, 2025)

CONCLUSION & NEXT STEPS

- Take-away
  - TFHE lowered entry barriers and increased enrollment for eligible students.
  - Quasi-experimental results showed that the increase in enrollment of eligible students induced a composition effect.
  - Infra-marginal students improved educational outcomes, while marginal students exerted low effort and had poor outcomes.
  - We built a dynamic model of major choice, graduation and endogenous effort. Marginal cost of effort was sensitive to income and ability, and OP fees.
- Next steps
  - Access tax data to include first labor market outcomes $\rightarrow$ allows to control for unobserved types (Arcidiacono and Miller, 2011).
  - Compute counterfactuals.

Part I
Appendix

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Section 8

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SUMMARY STATISTICS

	2012	2013	2014	2015	2016	2017
Enrollment						
N Students	165762	169257	169415	176027	180128	180302
Enrolled in platform	.260	.273	.280	.275	.280	.276
Enrolled out of platform	.338	.351	.346	.341	.330	.329
Not enrolled	.400	.374	.372	.382	.388	.394
Demograhics						
Family Income	3.5	3.7	3.9	4	4.1	4.5
Private School	.111	.111	.111	.109	.106	.105
Private Health	.268	.267	.268	.263	.262	.235
Father With College	.168	.169	.170	.171	.169	.184
Mother With College	.132	.132	.134	.135	.136	.139
Mother Employed	.414	.436	.460	.460	.461	.461
Funding						
Gratuidad	0	0	0	0	.236	.399
Subsidised loan	.281	.277	.273	.274	.223	.161
Other funding	.432	.515	.535	.614	.407	.254
No (public) funding	.407	.360	.346	.300	.273	.264

Notes: This table shows descriptive statistics on every student who enrolled and took the college entrance exam. Family income is categorized in 1-10 brackets.

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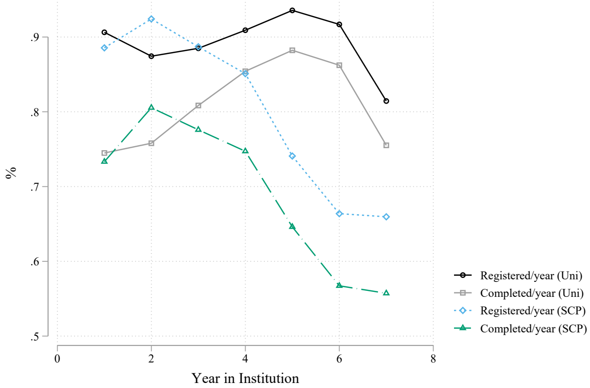
UM REGISTERED AND COMPLETED BY DEGREE TYPE



Notes: Amount of units of measure registered and completed wrt to yearly curriculum, by degree type (university or SCP).

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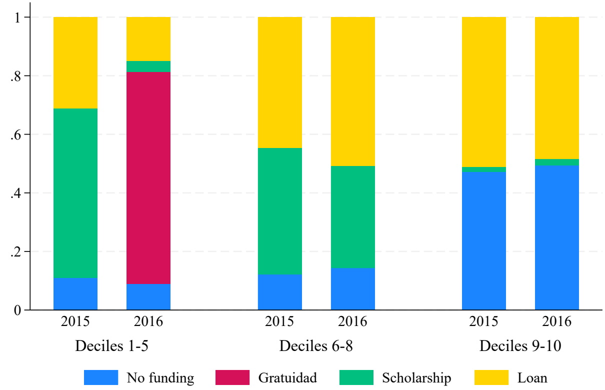
CHANGES IN FUNDING



Funding instruments by income decile (2015 vs 2016)

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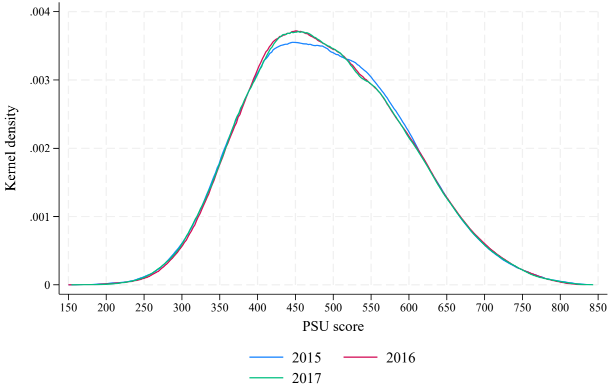
ENROLLMENT BY PSU



PSU score density

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ORDERED LOGIT

	index	
female	0.456***	(0.017)
Middle SES	0.121***	(0.019)
High SES	0.098***	(0.022)
PSU	0.534***	(0.019)
GPA	0.359***	(0.010)
OP fees	-0.029***	(0.002)
Rel. Ability	-0.007	(0.008)
Distance	-0.014	(0.009)
Cum. credits completed (t-1)	0.094***	(0.002)
Credits completed (t-1)	0.153***	(0.004)
Delay (t-1)	-1.628***	(0.010)
1 cred. left (t-1)	-1.712***	(0.038)
2 cred. left (t-1)	-0.810***	(0.026)
3 cred. left (t-1)	-0.531***	(0.032)
OP $\times$ female	0.011***	(0.002)
OP $\times$ middle SES	0.009***	(0.002)
OP $\times$ high SES	0.011***	(0.003)
OP $\times$ psu	0.013***	(0.001)
OP $\times$ gpa	0.003***	(0.001)
t= 2	-0.092***	(0.012)
t= 3	0.292***	(0.015)
t= 4	0.433***	(0.019)
t= 5	0.129***	(0.023)
t= 6	-0.658***	(0.027)
t= 7	-1.290***	(0.031)
Observations	1,416,805	
Mean of Dep. Variable	3.096	

Ordered logistic regression of discretised credit achievement (0-4). Controls include vector of characteristics, Institution and major FE, year enrolled FE and cumulated performance. PSU and GPU are standardised. Base category is low SES and t=1.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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DROPOUT PROBABILITIES

	dropout	
OP fees	0.083***	(0.003)
Rel. Ability	-0.058***	(0.013)
Distance	0.074***	(0.014)
Cumulated credits (t-1)	-0.112***	(0.002)
Credits (t-1)	-0.651***	(0.005)
Delay (t-1)	1.187***	(0.019)
female	-0.434***	(0.036)
Middle SES	-0.186***	(0.042)
High SES	-0.561***	(0.048)
PSU	0.009	(0.034)
GPA	-0.161***	(0.022)
OP $\times$ female	-0.003	(0.003)
OP $\times$ middle SES	0.025***	(0.004)
OP $\times$ high SES	0.073***	(0.005)
OP $\times$ psu	-0.033***	(0.002)
OP $\times$ gpa	-0.003*	(0.002)
t= 2	-0.340***	(0.011)
t= 3	-0.571***	(0.015)
t= 4	-0.613***	(0.020)
t= 5	0.117***	(0.024)
t= 6	1.655***	(0.028)
t= 7	3.864***	(0.036)
Observations	1,417,542	
Mean of Dep. Variable	0.180	

Logistic regression of choosing the outside option (dropping out) in period t. Controls include vector of characteristics, Institution and major FE, year enrolled FE and cumulated performance. PSU and GPU are standardised. Base category is low SES and t=1.

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FIXED COSTS

Fixed Costs are specified as a conditional logit

$$FC_j(x_{it}) = \alpha_p OP_{ij} + \sum_m \alpha_{pm} OP_{ij} Z_{im} + \sum_m \sum_n \alpha_{mn} Z_{im} Z_{jn} + \sum_m \sum_n \alpha_{gm} Z_{gm} Z_{in}$$
$$+ \mathbf{Z_g}' \alpha_{\mathbf{G}} + \sum_{\mathbf{m}} \sum_{\mathbf{k}} \alpha_{\mathbf{km}} \mathbf{M_{ij,k} Z_{im}} + \mathbf{M_{ij}}' \alpha_{\mathbf{m}} + \alpha_{\mathbf{field(j)}} + \alpha_{\mathbf{inst(j)}},$$

where $M_{ij} = (D_{ij}, A_{ij})$ is a vector of student–program matched variables. D_{ij} is a dummy for the institution being in a different region (distance proxy), and A_{ij} is the student's relative ability in program j.

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WAGE EQUATION

$$\log(\text{wage}_j(x_{it})) = \alpha_0^w + \alpha_{Zi}^w \text{female}_i + \alpha_e^w \text{exper}_{it} + \alpha_{e2}^w \text{exper}_{it}^2 + \alpha_j^w + \lambda_R^w + \alpha_{Rj}^w R_i \otimes j + \varepsilon_{ijt}$$

with $\varepsilon_{ijt} \sim \mathcal{N}(0, \sigma_w^2)$. R_i is a vector of dummy variables corresponding to the 16 regions of Chile.

WAGE EQUATION

	log wage	
Female	-0.291***	(0.007)
Experience	0.009***	(0.000)
Experience sq	0.000***	(0.000)
Administración y Comercio	0.408***	(0.121)
Agropecuaria	0.019	(0.119)
Arte y Arquitectura	-0.409***	(0.134)
Ciencias Básicas	1.253***	(0.274)
Ciencias Sociales	0.541***	(0.154)
Derecho	0.257	(0.267)
Educación	0.015	(0.079)
Humanidades	0.686	(0.506)
SCP	0.400***	(0.083)
SCP-Gratuidad	-0.149	(0.131)
Salud	0.351***	(0.090)
Tecnología	0.258***	(0.097)
Tarapacá	0.489***	(0.027)
Antofagasta	0.654***	(0.029)
Atacama	0.498***	(0.026)
Coquimbo	0.253***	(0.025)
Valparaíso	0.261***	(0.023)
O'Higgins	0.266***	(0.024)
Maule	0.132***	(0.024)
Biobío	0.209***	(0.023)
Araucanía	0.068***	(0.024)
Los Lagos	0.184***	(0.024)
Aysén	0.398***	(0.033)
Magallanes	0.535***	(0.030)
Metropolitana	0.380***	(0.023)
Los Ríos	0.199***	(0.028)
Arica	0.187***	(0.037)
Outside	-0.408***	(0.027)
Private	0.377***	(0.021)
CRUCH	0.644***	(0.019)
Observations	104588	

Mincerian wage regression
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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MARGINAL COSTS

	MC		log(MC)	
OP fees	-0.001***	(0.000)	-0.051	(0.042)
Distance	-0.000	(0.000)	0.072**	(0.031)
Delay (t-1)	-0.003***	(0.001)	-0.415**	(0.187)
t=1	-0.065***	(0.006)	-4.553***	(1.135)
t=2	-0.065***	(0.006)	-4.667***	(1.138)
t=3	-0.063***	(0.006)	-4.491***	(1.139)
t=4	-0.046***	(0.006)	-2.003*	(1.141)
t=5	-0.024***	(0.006)	-1.392	(1.157)
OP x female	0.001**	(0.000)	0.066	(0.041)
OP x middle SES	-0.000	(0.000)	-0.003	(0.047)
OP x high SES	0.000	(0.000)	0.014	(0.044)
OP x psu	-0.000	(0.000)	0.005	(0.024)
OP x gpa	-0.000	(0.000)	-0.009	(0.016)
OP (during HE)	0.000	(0.000)	-0.028	(0.058)
Delay (t-1) x female	-0.000	(0.001)	-0.177	(0.177)
Delay (t-1) x middle SES	0.004***	(0.001)	0.208	(0.211)
Delay (t-1) x high SES	-0.002	(0.001)	0.027	(0.266)
Delay (t-1) x psu	-0.001	(0.001)	-0.081	(0.101)
Delay (t-1) x gpa	-0.000	(0.001)	-0.199*	(0.104)
Observations	11,322		10,812	
ymean				

Standard errors in parentheses

MC heterogeneity

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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