Labor Economics

Human Capital vs Signaling

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Outline

1. Theory

2. Empirical Evidence

Theory

Competing Theories

- We've seen the there are returns to education, but this work cannot identify the *mechanism*
- Two possible theories (not exclusive):
  - **Human Capital:** Education increases productivity. Since workers are paid their marginal product, this results in higher wages
  - **Signaling:** Worker's productivity is unknown to firms. Education is a way for workers to credibly signal their high productivity (but it doesn't improve productivity itself). This results in higher wages

Signaling Model

- Signaling only makes sense if we have two things:
    - Heterogeneity: workers have different productivity
    - Asymmetric information: the firms don't know the worker's productivity
- Imagine a world where there are high productivity (H) and low productivity (L) workers.
    - Workers know their type, but firms don't
    - You are an employer and someone comes looking for a job. What wage should you pay them?

Signaling Model

- Let's take a simple example
  - Suppose that a fraction θ of workers are H and $1 - \theta$ are L
  - Suppose that the marginal product for the workers are y_H and y_L, where $y_H > y_L$
- If the firm could observe the type, then you should pay them their marginal product
  - H types get paid $w_H = y_H$ and L types get paid $w_L = y_L$
- If the firm cannot observe the type, the best you can do is pay the *expected* output
  - Pay <u>every</u> worker $\bar{w} = \theta \cdot y_H + (1 - \theta) \cdot y_L$

Signaling Model

- Now, let's introduce a signal: a worker can pay a cost c and get a signal that tells the firm they are a high worker
  - If you don't get the signal, the firm assumes you are a low worker
  - If $w_H - c > w_L$, then everybody gets the signal
  - If $w_H - c < w_L$, then nobody gets the signal
- But if everybody does the same thing... we're back to where we started! The signal doesn't tell us anything
  - Example: suppose that to show you were high productivity, you just have to wear a blue shirt to the interview. What would happen?

Signaling Model

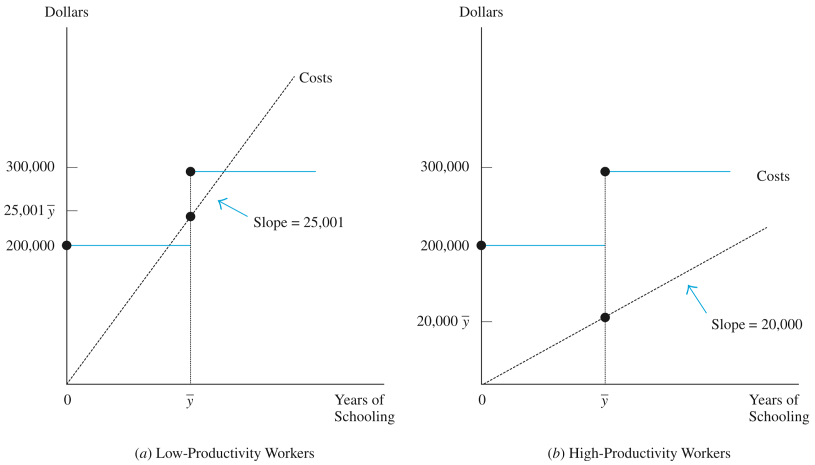
- For the signal to work, it has to be *more* costly for the low types
    - Let cost be c_H for H and c_L for L, where $c_H < c_L$
- For H, get the signal if: $w_H - c_H > w_L$
- For L, get the signal if: $w_H - c_L > w_L$
- To get an equilibrium where H get signal and L don't, we need:

$$w_H - c_H > w_L > w_H - c_L$$
$$\implies c_H < w_H - w_L < c_L$$

- We call this a **separating equilibrium**

Graphical Example

Figure 1: Signaling Example



Source: GB, Figure 6.7

Applying Signaling

- Challenge is that both signaling and human capital theories say that there are returns to education
  - Hard to empirically distinguish since we don't often observe HC, productivity, or the firm's information
- Notice that signaling doesn't change the worker's productivity
  - Education clearly produces human capital at younger age. Is completing kindergarten a meaningful signal?
  - But signaling could play a role in high school and, especially, college
- It's clear that you can learn something at college, especially those in technical fields (e.g. coding, lab work, metrics)
  - Is college teaching you skills that the labor market actually values? Should firms just teach you the skills they require?

Discussion

- College enrollment is declining and tuition is rising. What does this tell us about the signal?
- If the signaling theory was true, what are the policy implications for higher education reform?
- How does signaling interact with the issues of inequality and mobility?
- Thoughts on Bryan Caplan's article **"What's College Good For?"**

Empirical Evidence

The Signaling Value of a High School Diploma

Damon
Clark

Paco
Martorell

***JPE*, 2014**

Paper Overview

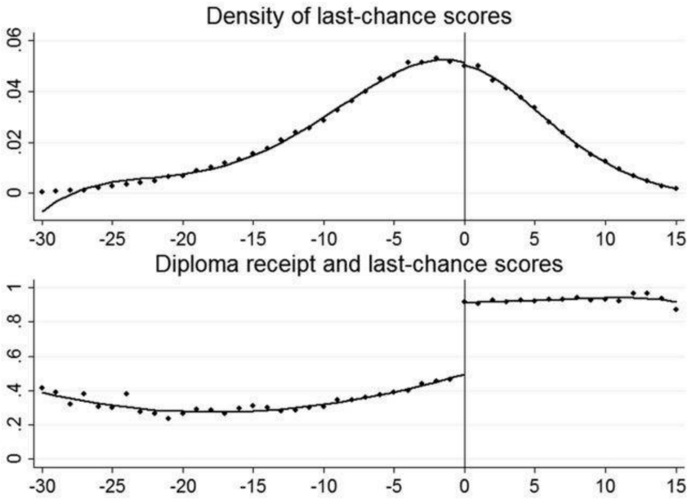
- High school diploma interesting for two reasons:
  1. Most commonly held credential in the US
  2. Measure of schooling that does not affect productivity
- The diploma itself is just a piece of paper $\implies$ has a pure signaling effect
- Ideal experiment: randomize who gets a diploma

Setting

- In Texas, must take a high school exit exam to graduate and receive diploma
- Students typically take the exam in 10th or 11th grade
  - Allowed to re-take the exam
- Focus on students on those who re-take exam at the end of 12th grade
  - Last chance to re-take the exam
- Those who barely pass get the diploma. Those who barely fail will not get the diploma
  - Natural experiment: regression discontinuity
- Data: 1993-1997 test takers with earnings until 2004 (i.e. 7-11 years post-HS)

First-Stage

Figure 2: RD First Stage

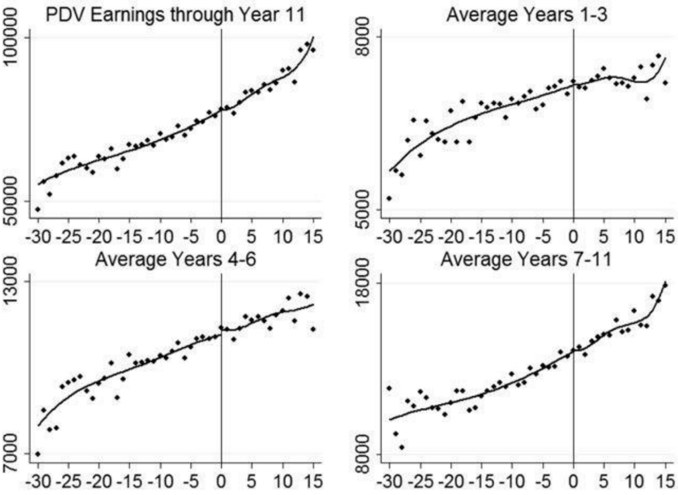


Source: Clark and Martorell (2014), Figure 1

Validity

- Teachers could be manipulating scores since stakes are high
  - No bunching in the distribution
- Could look at earlier years (e.g. barely passers/failers in 11th grade)
  - Failing could affect drop-out, which would result in different years in schooling
  - The sample students have usually done everything to graduate except pass the exam
- Fuzzy RD - instrument (passing score) has to satisfy exclusion restriction
  - Passing score only matters to earnings through the diploma
  - Could affect whether you go for a GED instead, which may affect earnings. Find this effect is too small

Figure 3: RD Plots



Source: Clark and Martorell (2014), Figure 2

Results

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 D_i + \beta_3 (X_i \times D_i) + \varepsilon_i$$

Table 1: RD Estimates

	(1)
Years 1–3 (mean earnings: 7,006)	9.7
	(110.8)
Years 4–6 (mean earnings: 11,055)	18.2
	(165.4)
Years 7–11 (mean earnings: 13,732)	134.6
	(237.6)
All years pooled (mean earnings: 10,743)	58.0
	(151.4)
PDV earnings through year 11 (mean: 75,986)	318.6
	(1,084.9)
Baseline covariates?	No
Degree of test score polynomial	1
Polynomial specification	Unrestricted

Source: Clark and Martorell (2014), Table 3

Conclusion

While creative theorists may be able to construct some variant of the signaling model that accounts for this result*,* *we view this evidence as a strong challenge to those who contend that high school completion is valued by employers as a signal of productivity. Given the evidence in Bishop (1988) concerning the response rates of schools to inquiries about students' academic records, one expects physical possession of a diploma to have real value in a world in which high school completion is a valuable signal. We find* ***no evidence that Texas students live in such a world****.*

The Effect of Human Capital on Earnings

Evidence from a Reform at Colombia's Top University

Carolina
Arteaga

JPubE, 2018

Discussion: Arteaga (2018)

- Tables: Tab. 1 Tab. 3 Tab. 4
- Figures: Fig. 1 Fig. 3 Fig. 4 Fig. 5

Take-away

- So far, two papers that reject signaling
- Reading: WSJ article **“Job Hunting? Dig Up Those Old SAT Scores”**
  - Why would employers want a *pre*-college test if they are hiring college graduates?
- Thought experiment: what if everyone had to re-take the SAT (or take the GRE) at the end of college?
  - Something like this happened in Colombia!

The Big Sort: *College Reputation and Labor Market Outcomes*

W. Bentley **MacLeod**

Evan **Riehl**

Juan **Saavedra**

Miguel **Urquiola**

AEJ:AE, 2017

Motivation

- Choosing college is a major decision:
  - What skills can I learn in college?
  - How does the college's reputation affect job prospects?
- The "big sort": choosing a college and find first job after graduation
- Earnings for college graduates correlated with college's reputation (even after controls)
- Do high reputation colleges provide more skill or send a stronger signal about ability?

Paper Overview

- Use natural experiment in Colombia: staggered introduction of national college exit exam
- Exit exams provide signal of skill of college graduate
- **Prediction:** employers should rely less on college reputation as a signal of ability since they have a better measure now
- **Punchline:** prediction holds, but they find something surprising and inconsistent with signaling model – college reputation premium increases over time
    - Reputation may play bigger role than signaling
    - Makes understanding the big sort even more important

Model

- In the paper, there is a formal model, but let's just go through the story
    - The model gives us *predictions* that we can test. That's the point of this part
- The "big sort" involves two parts.
    - First, students have to choose and attend college (matriculation).
    - Second, students finish college and look for a job (graduation).

Matriculation

- A student's admissions test score (e.g. SAT) is a *noisy* measure of their ability
- Each college has a reputation. Let reputation be the average admissions test score of its graduates (e.g. mean SAT score for Columbia is 1500)
    - Tests are taken *before* students even attend college. Reputation captures pre-college quality of students who go there
    - More selective schools will pick students with higher scores, which gives them a higher reputation

Graduation

- When a student graduates, they learn something at college:

  Post-College Skill = Pre-College Ability + College Value-Add

- Firms want to hire graduates but cannot observe the student's skill
- Need to predict the skill of the student given their college's reputation
  - e.g. "given that Columbia has an average SAT score of 1500, how smart is the average person that goes to Columbia?"
- Set wages according to expected skill

Working

- Employers are constantly learning about the *true* skill level of their workers
- Rely on three sources of information
  1. The average skill quality of a college's graduates (y_R)
  2. A *noisy* signal of a worker's skill when they first hire the worker (y_H)
  3. A *noisy* signal of a worker's skill while the person is employed at the firm (y_E)
- Expected skill (i.e. wages) is a weighting of these three factors:

$$w = \theta_R y_R + \theta_H y_H + \theta_E y_E$$

- Over time, you should only rely on the output they produce while working at the firm (i.e. $\theta_R, \theta_H \to 0$ and $\theta_1 \to 1$)

Regression

- Model implies that there is a **return to reputation** and a **return to ability**, and these vary over time
- Can run the following regression for a person i from school s at time t years after graduation:

$$w_{it} = r_t R_{s_i} + a_t \tau_i + e_{it}$$

  - where w is the person's wage
  - R is the person's college reputation
  - τ_i is the person's test score (proxy for ability)

Predictions

- The introduction of an exit exam means that firms have a better way of observing the worker's skill level when they first hire a worker
  - This means they should rely less on college reputation when setting wages
- The return to reputation should fall over time
  - Firms observe reputation at the time of hire, so they've already incorporated it into wages
  - They learn more about the worker's (unobservable) skill over time, so the return to ability should increase over time

Prediction for Returns

- Let $\delta_i = 1$ if student i has exit exam:

$$w_{it} = (1-\delta_i)\left(r_t R_{s_i} + a_t \tau_i\right) + \delta_i \left(r_t^{exit} R_{s_i} + a_t^{exit} \tau_i\right) + e_{it}$$

$$= \left(r_t R_{s_i} + a_t \tau_i\right) + \delta_i \left(\underbrace{\left(r_t^{exit} - r_t\right)}_{\beta_t^r} R_{s_i} + \underbrace{\left(a_t^{exit} - a_t\right)}_{\beta_t^a} \tau_i \right) + e_{it}$$

- **Prediction:** introduction of exit exam reduces the return to college reputation ($\beta_t^r < 0$) and increases the return to ability ($\beta_t^a > 0$)

Prediction for Wage Growth

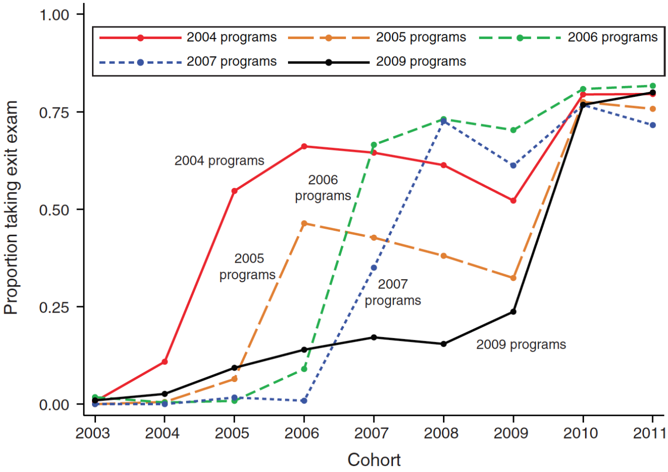
$$w_{it} = r_t R_{s_i} + a_t \tau_i + e_{it}$$

1. Return to reputation (r_t) falls over time
2. Return to ability (a_t) rises over time

Setting

- Study colleges in Colombia
- Students take standardized exam for college admissions called Icfes
  - Like SATs, but most people take it (even if they don't intend on applying to college)
  - Play a major role in admissions; many schools only consider test score
- From 2004-2007, major-specific exit exams were rolled out gradually
  - Initial fields were more popular majors
  - In 2009, exit exams became mandatory for graduation for everyone

Figure 4: Roll-out of Exit Exams



Source: MacLeod et al. (2017), Figure 2

Identification

- Gradual roll-out provides natural experiment
  - 2003–2004: no programs had exams
  - 2005–2009: some programs had exams (“2004 programs”, 90% of graduates)
  - 2010–: all programs had exams (“2009 programs”, 10% of graduates)
- How does the returns to reputation and ability change for the 2004 programs relative to the 2009 programs?
  - Diff-in-diff in **slopes**

Identification

- Treatment is getting the exam
  - Treatment group are the programs that got it early (2004 programs)
  - Control group are the program that got it late (2009 programs)
- Usual DID looks at how treatment affects average outcome
  - This DID looks at how treatment affects the value of a coefficient (slope)

Estimation: Prediction 1

- First step: estimate program-cohort specific returns

$$w_{ipct} = \underbrace{d_{pc}}_{\substack{\text{Fixed}\\\text{Effects}}} + \underbrace{f_p(t)}_{\substack{\text{Experience}\\\text{Program}\\\text{Interaction}}} + \underbrace{r_{pc}}_{\substack{\text{Returns}\\\text{to educ}}} R_{s_i} + \underbrace{a_{pc}}_{\substack{\text{Returns}\\\text{to ability}}} \tau_i + e_{ipct}$$

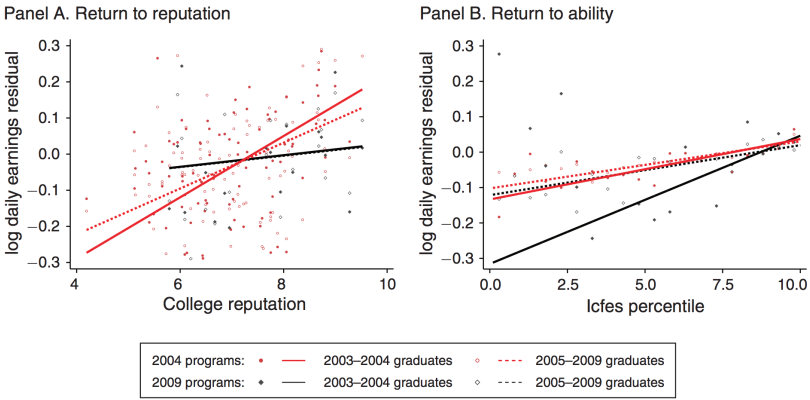
- Second step: estimate change in returns due to treatment (DID)

$$\hat{r}_{pc} = \mu_p + \mu_c + \beta^r \delta_{pc} + e^r_{pc}$$
$$\hat{a}_{pc} = \nu_p + \nu_c + \beta^a \delta_{pc} + e^a_{pc}$$

where δ_{pc} indicates that program-cohort had exit exams

DID Graph

Figure 5: DID in Slopes



Source: MacLeod et al. (2017), Figure 3

DID Estimation

$$w_{it} = \left(r_t R_{s_i} + a_t \tau_i\right) + \delta_i \left(\underbrace{\left(r_t^{exit} - r_t\right)}_{\beta_t^r} R_{s_i} + \underbrace{\left(a_t^{exit} - a_t\right)}_{\beta_t^a} \tau_i \right) + e_{it}$$

$$= r_t R_{s_i} + a_t \tau_i + \beta_t^r \left(R_{s_i} \times \delta_i\right) + \beta_t^a \left(\tau_i \times \delta_i\right) + e_{it}$$

Table 2: DID Estimation

		Experience and cohort controls	
Dependent variable: log average daily earnings	Benchmark specification (1)	Within experience (2)	Linear trends (3)
Reputation $\times$ δ_{pc}	−0.041	−0.033	−0.034
	(0.017)	(0.015)	(0.028)
Icfes $\times$ δ_{pc}	0.017	0.018	0.012
	(0.006)	(0.007)	(0.009)
Observations	581,802	267,924	267,924

Source: MacLeod et al. (2017), Table 3

Estimation: Prediction 2

- To estimate the returns over time ($t =$years after grad):

$$w_{it} = d_{c_i t} + r_0 R_{s_i} + r\left(R_{s_i} \times t\right) + a_0 \tau_i + a\left(\tau_i \times t\right) + e_{it}$$

- Estimate for 2008-2009 graduates for first three years of employment
- Not causal. Testing for prediction: $r < 0$ and $a > 0$

Results

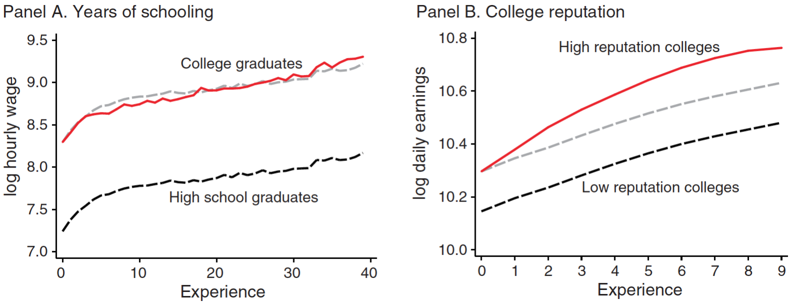
Table 3: Returns with Experience

Dependent variable: log average daily earnings	(1)	(2)	(3)	(4)
Reputation	0.101	0.071	0.079	0.055
	(0.017)	(0.017)	(0.017)	(0.016)
Reputation $\times$ t	0.017	0.017	0.012	0.008
	(0.003)	(0.003)	(0.003)	(0.002)
Icfes		0.033	0.024	0.017
		(0.003)	(0.002)	(0.002)
Icfes $\times$ t			0.006	0.002
			(0.001)	(0.001)
Observations	83,492	83,492	83,492	83,492
R^2	0.179	0.189	0.190	0.306
Number of colleges	130	130	130	130
Extra controls				Yes

Source: MacLeod et al. (2017), Table 7

Results

Figure 6: Reputation Returns Over Time



Source: MacLeod et al. (2017), Figure 4

Take-away

- Mixed findings for their model
  - Reputation plays a role and the return to reputation decreased after the exit exams (as predicted)
  - Returns to reputation increase with experience (inconsistent with the model)
- Compare to Arteaga (2018): same country, same time period... quite different conclusions!
  - Which one do you believe more? Can both conclusions be correct?

Next Steps

- Education can raise education, but we're not quite sure of the mechanism
- College can play an important in mobility, but access is important to consider
- This part of the class has been about inequality and opportunity – in particular, how can we improve outcomes for the poorest households
    - Send them to college, move them to better neighborhoods etc
    - Why not just give them money?
- Next class: **welfare programs**

Appendix

Arteaga (2018)

Table 1
First stage – The effect of the reform on instruction and class quality.
Source: Annual bulletin – Universidad de los Andes & Department of economics.

Dep variable	Degree duration		No. of credits	Class size		HS test scores		Graduation rates	
	Econ	Buss	Econ	Econ	Buss	Econ	Buss	Econ	Buss
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post	− 1.038**	− 0.916***	− 24.37**	8.56	− 22.15	− 1.396	36.42	0.0192	0.00097
	[0.367]	[0.262]	[6.751]	[14.74]	[32.20]	[40.97]	[71.51]	[0.0635]	[0.0496]
Trend pre	0.0943	− 0.0821	3.317*	1.024	2.086	− 6.272	− 1.655	− 0.0135	− 0.00503
	[0.119]	[0.0528]	[1.637]	[2.248]	[4.124]	[5.546]	[7.913]	[0.0110]	[0.00606]
Trend post	− 0.121***	− 0.0309	− 0.545	0.0952	− 2.309	12.90***	19.93***	0.00692	0.0145**
	[0.0280]	[0.0266]	[1.637]	[2.248]	[1.899]	[3.755]	[3.801]	[0.00596]	[0.00606]
Constant	9.716***	10.51***	160.8***	68.08***	64.35***	637.6***	557.0***	0.842***	0.789***
	[0.222]	[0.181]	[5.430]	[9.403]	[5.537]	[21.28]	[16.13]	[0.0438]	[0.0376]
Obs	18	18	10	16	16	21	21	20	20
R squared	0.868	0.881	0.867	0.233	0.171	0.45	0.672	0.163	0.427

Source: Arteaga (2018), Table 1 Back

Arteaga (2018)

Table 3
Baseline results. Effect of the reform on wages.
Source: Ministry of Education OLE and SPADIES.

Dep var: Ln wage	(1)	(2)	(3)	(4)	(5)	(6)
Panel a: Economics						
Post*Andes	− 0.163**	− 0.161**	− 0.167***	− 0.164**	− 0.164**	− 0.161**
	[0.0500]	[0.0501]	[0.0505]	[0.0505]	[0.0501]	[0.0501]
Post	0.0817**	0.0819**	0.0721*	0.0744*	0.0810*	0.0865*
	[0.0293]	[0.0292]	[0.0311]	[0.0310]	[0.0366]	[0.0360]
Andes	0.312***	0.301***	0.312***	0.300***	0.311***	0.300***
	[0.0304]	[0.0301]	[0.0304]	[0.0301]	[0.0304]	[0.0301]
Experience	0.135***	0.154***	0.137***	0.154***	0.135***	0.156***
	[0.00842]	[0.0173]	[0.00841]	[0.0173]	[0.0127]	[0.0188]
Experience squared		− 0.00424		− 0.004		− 0.00429
		[0.00431]		[0.00429]		[0.00431]
Female		− 0.0912***		− 0.0908***		− 0.0914***
		[0.0223]		[0.0223]		[0.0224]
Constant	14.16***	14.20***	14.13***	14.17***	13.96***	14.19***
	[0.0197]	[0.0238]	[0.0495]	[0.0511]	[0.0846]	[0.0383]
Cohort control	N	N	Y	Y	N	N
Year D	N	N	N	N	Y	Y
Clusters	11	11	11	11	11	11
Obs	3,621	3,621	3,621	3,621	3,621	3,621
R − sq	0.157	0.165	0.157	0.165	0.159	0.167

Source: Arteaga (2018), Table 3 Back

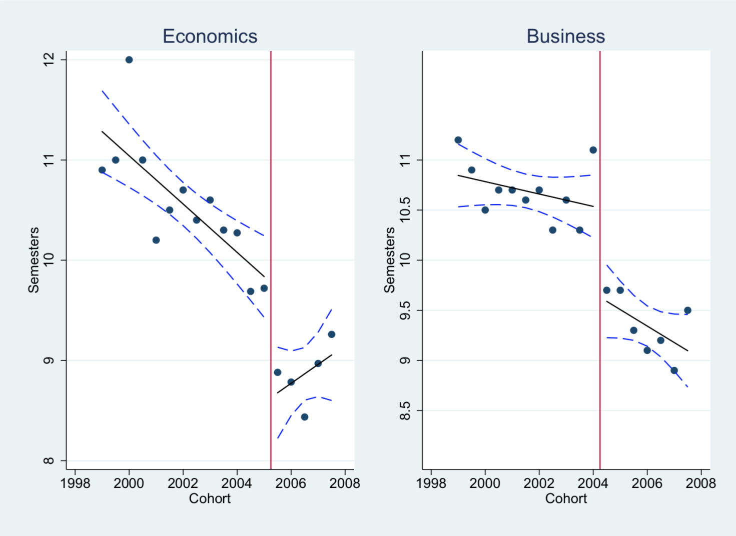
Arteaga (2018)

Table 4
Placebo coefficients.
Source: Ministry of Education OLE and SPADIES.

Diff in Diff coefficient	(1)	(2)	(3)	(4)	(5)	(6)
Panel a: Economics						
Andes	− 0.163	− 0.161	− 0.167	− 0.164	− 0.164	− 0.161
Placebo school 1	− 0.145	− 0.145	− 0.150	− 0.148	− 0.148	− 0.146
Placebo school 2	− 0.127	− 0.104	− 0.129	− 0.106	− 0.123	− 0.099
Placebo school 3	− 0.041	− 0.053	− 0.045	− 0.045	− 0.044	− 0.057
Placebo school 4	− 0.039	− 0.030	− 0.032	− 0.035	− 0.037	− 0.031
Placebo school 5	− 0.026	− 0.024	− 0.022	− 0.021	− 0.027	− 0.025
Placebo school 6	0.080	0.071	0.081	0.074	0.078	0.070
Placebo school 7	0.081	0.073	0.087	0.077	0.085	0.075
Placebo school 8	0.106	0.104	0.109	0.107	0.108	0.103
Placebo school 9	0.113	0.105	0.118	0.109	0.111	0.106
Placebo school 10	0.197	0.220	0.200	0.222	0.206	0.230
Cohort control	N	N	Y	Y	N	N
Year D	N	N	N	N	Y	Y
Clusters	11	11	11	11	11	11
Obs	3,621	3,621	3,621	3,621	3,621	3,621

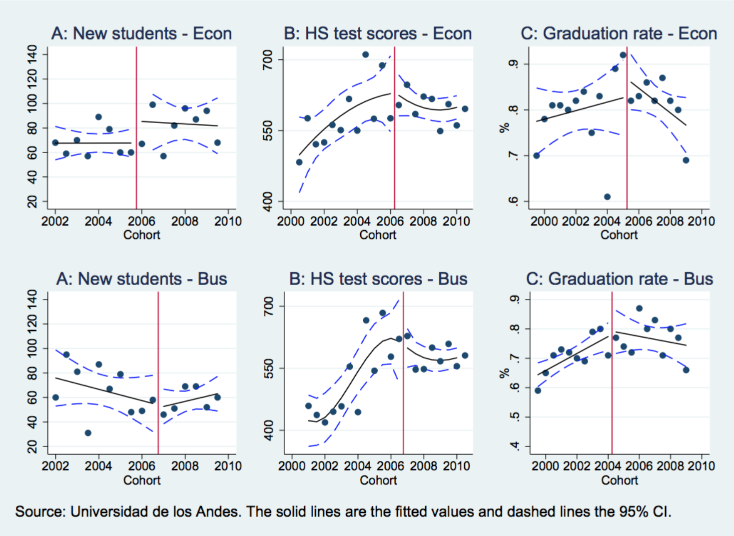
Source: Arteaga (2018), Table 4 Back

Arteaga (2018)



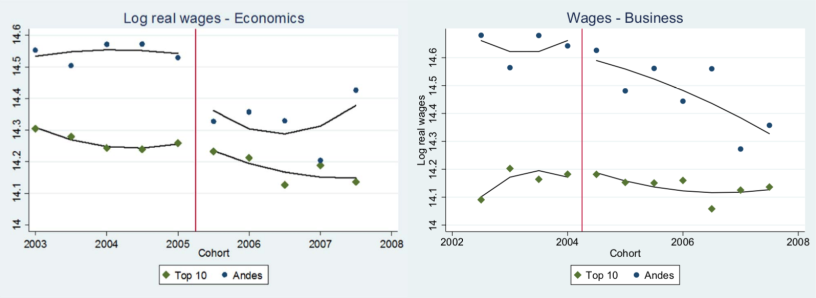
Source: Arteaga (2018), Figure 1 Back

Arteaga (2018)



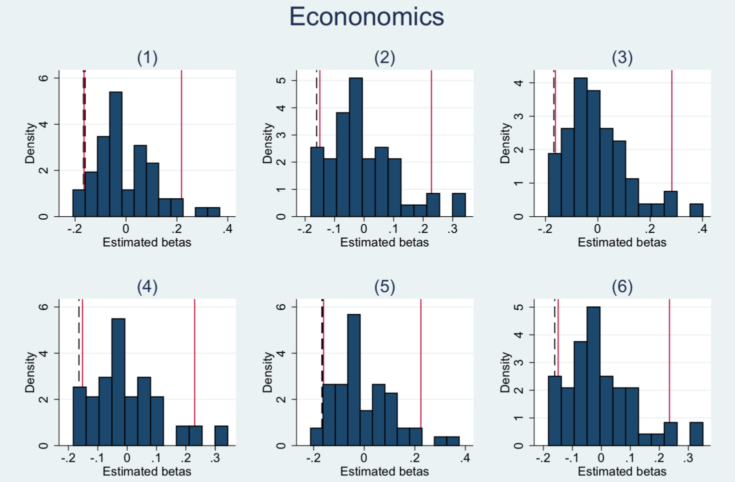
Source: Arteaga (2018), Figure 3 Back

Arteaga (2018)



Source: Arteaga (2018), Figure 4 Back

Arteaga (2018)



Solid lines represent the 5th and 95th percentile. The dashed line represents my treatment effect.

Source: Arteaga (2018), Figure 5 Back

References

References i

Arteaga, C. (2018). “The Effect of Human Capital on Earnings: Evidence from a Reform at Colombia’s Top University”. In: *Journal of Public Economics* 157, pp. 212–225.

Clark, D. and P. Martorell (2014). “The Signaling Value of a High School Diploma”. In: *Journal of Political Economy* 122.2, pp. 282–318.

MacLeod, W. B. et al. (2017). “The Big Sort: College Reputation and Labor Market Outcomes”. In: *American Economic Journal: Applied Economics* 9.3, pp. 223–261.