Freshmen Teachers and College Major Choice: Evidence from a Random Assignment in Chile

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Agenda

Motivation

The Model

Data

Results

Conclusion

Motivation

There is a broad literature in educational economics concerning college major choices.

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Notwithstanding, research focusing on the causal effects of teachers on college major choices is scarce.

Main challenge: teachers are usually endogenously chosen by students.

The Questions

Can some instructors have a causal impact on major choices?
(Or are majors mostly predetermined by students preferences?)

If so, how/why?

FORTHCOMING: *Can instructors affect early labor market outcomes?*

Previous Papers

- Bettinger and Long (2005) identify the effect of having a gender-matching instructor on the probability of majoring in that instructor's field.

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- Price (2010) repeats an analogous exercise, but also considers race-matching.
- Repeating this estimation strategy, Bettinger and Long (2010) study how adjunct instructors impact the probability of majoring in that particular instructor's field.

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- Exploits a quasi-experimental setting in freshmen course assignment in a large Chilean university.
- Makes use of 10 years of cross-section and detailed microdata on students and teachers. This combines administrative records of the university and the Chilean Ministry of Education.
- Identifies the causal effect that teachers may have on students' major choice.
- Identifies the characteristics of these teachers that make students more prone to majoring in Economics.

Context

- Using a centralized platform, students apply to different *program* × institution combinations, and are assigned to a program according to their test scores.
- A program is *not* a major.
- Students have a *common core* year, in which they are randomly assigned to their classes.
- By the end of their second year, they have to choose their major.
- Then, they have 3 more years of coursework in their major to fulfill the requirements for their degree (total program duration of 5 years).

The Model

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Suppose that there is a tacit net utility of choosing Economics over Business for student i and denote it as U_i. Thus, we have that

$$Y_i = \begin{cases} 1 & U_i > 0 \\ 0 & U_i \leq 0 \end{cases}. \tag{1}$$

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$$Y_i = \begin{cases} 1 & U_i > 0 \\ 0 & U_i \leq 0 \end{cases}. \tag{1}$$

Now we impose some structure on U_i, letting it be

$$U_i = \beta_0 + \sum_{j \in J} \beta_j T_{ij} + \mathbf{XB} + \varepsilon_i, \tag{2}$$

where T_{ij} is 1 if student i was assigned to teacher j in set J and 0 if not, $\mathbf{X}$ is a set of observed characteristics and ε_i is an unobserved error component.

The Model (contd')

Suppose now that $\varepsilon_i \sim N(0, \sigma_t^2)$, where t indexes years/cohorts.

Then, substituting (2) in (1) we get

$$Y_i = \begin{cases} 1 & \beta_0 + \sum_{j \in J} \beta_j T_{ij} + \mathbf{XB} + \varepsilon_i > 0 \\ 0 & \beta_0 + \sum_{j \in J} \beta_j T_{ij} + \mathbf{XB} + \varepsilon_i \le 0 \end{cases}.$$

But $\beta_0 + \sum_{j \in J} \beta_j T_{ij} + \mathbf{XB} + \varepsilon_i > 0 \iff \varepsilon_i > -\left(\beta_0 + \sum_{j \in J} \beta_j T_{ij} + \mathbf{XB}\right)$ and the odds of this event are equal to

$$\mathbb{P}\left(Y_i = 1 | \{T_{ij}\}_{j \in J}, \mathbf{X}\right) = \Phi\left(\frac{\beta_0 + \sum_{j \in J} \beta_j T_{ij} + \mathbf{XB}}{\sigma_t}\right),$$

where Φ is a cumulative standardized Gaussian distribution.

Therefore, we finally obtain a reduced-form probit model described by

$$Y_i = \beta_0 + \sum_{j \in J} \beta_j T_{ij} + \mathbf{XB} + \varepsilon_i. \tag{3}$$

Identification Strategy

Teacher assignment is random, conditional on program. As our sample consists uniquely of students of the Commercial Engineering career, assignment is completely random among them, i.e.

$$\mathbb{P}(T_{i,j} = 1 | i \in \text{Career}) = \mathbb{P}(T_{i',j} = 1 | i' \in \text{Career}) \qquad \forall j \in J.$$

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Therefore, as $\mathbb{E}(T_{ij}\varepsilon_i) = 0 \ \forall j \in J$, the set of estimated parameters $\{\hat{\beta}_j\}_{j \in J}$ is completely unbiased and we may obtain a causal effect of each teacher on the chances of choosing Economics as a major.

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Estimation of the parameters in equation (3) by MLE.

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Estimation of the parameters in equation (3) by MLE.

Note: t subscripts are omitted as they are images of i (and no dynamics are considered).

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Table 1: Summary Statistics

	Obs.	Mean	Std. Dev.	Min.	Max.
Econ. Major	1561	.4144779	(.4927895)	0	1
ECON101 Grade	1829	4.793166	(.9228158)	1.2	7
Entrance Score	1827	723.9126	(23.40134)	679.1	830.2
Female	1829	.3870968	(.4872193)	0	1
School GPA	1827	6.414926	(.2583345)	5.1	7

The Data...

	Observations	Mean	Standard Deviation	Min.	Max.
Prof. 2	1829	.0437397	(.2045714)	0	1
Prof. 3	1829	.0732641	(.2606407)	0	1
Prof. 4	1829	.1388737	(.3459093)	0	1
Prof. 5	1829	.1098961	(.3128458)	0	1
Prof. 6	1829	.0464735	(.2105658)	0	1
Prof. 7	1829	.1394204	(.3464795)	0	1
Prof. 8	1829	.0656096	(.2476662)	0	1
Prof. 9	1829	.0415528	(.1996194)	0	1
Prof. 10	1829	.1306725	(.337134)	0	1
Prof. 11	1829	.1170038	(.3215128)	0	1
Prof. 12	1829	.0322581	(.176733)	0	1
Prof. 13	1829	.0311646	(.1738098)	0	1
Block. 2	1829	.2121378	(.4089337)	0	1
Block. 3	1829	.1618371	(.368402)	0	1
Block. 4	1829	.0896665	(.2857815)	0	1
Block. 5	1829	.0426463	(.2021135)	0	1
Block. 6	1829	.049754	(.2174957)	0	1
Week Days	1829	1.300164	(.4584545)	1	2
Year 2006	1829	.0978677	(.2972169)	0	1
Year 2007	1829	.0967742	(.2957309)	0	1
Year 2008	1829	.1109896	(.3142052)	0	1
Year 2009	1829	.0995079	(.2994246)	0	1
Year 2010	1829	.1328595	(.3395156)	0	1
Year 2011	1829	.0978677	(.2972169)	0	1
Year 2012	1829	.0448332	(.2069943)	0	1
Year 2013	1829	.1109896	(.3142052)	0	1
Year 2014	1829	.1388737	(.3459093)	0	1
Failed ECON101	1829	.1246583	(.3304214)	0	1

The Data: Graphs

Figure 3: Entrance Score by Major

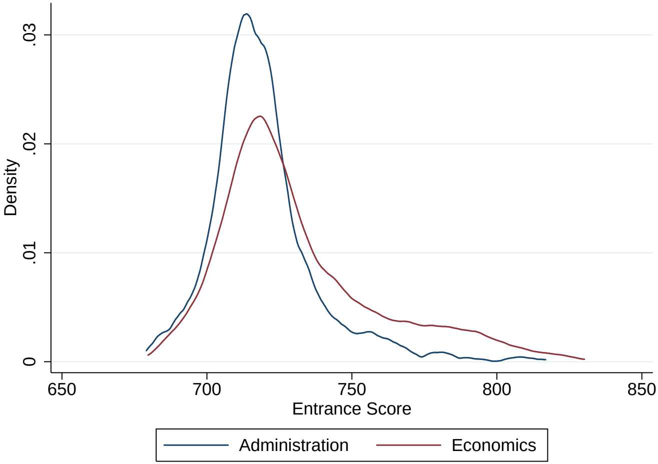

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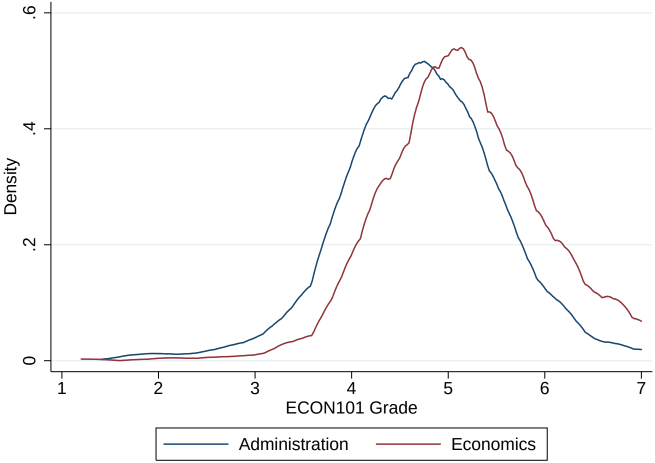
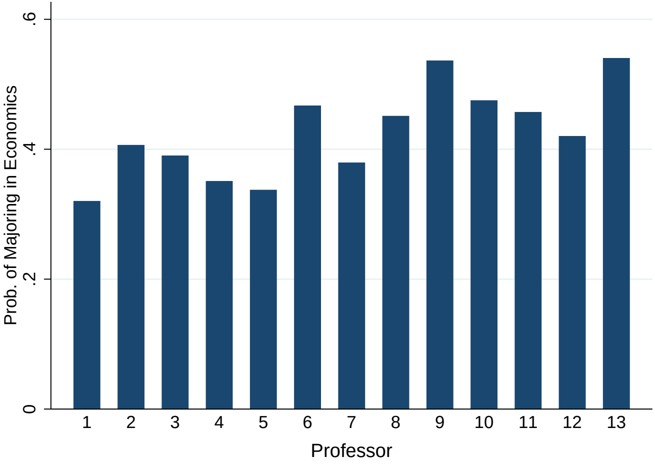
Figure 4: ECON101 Grade by Major



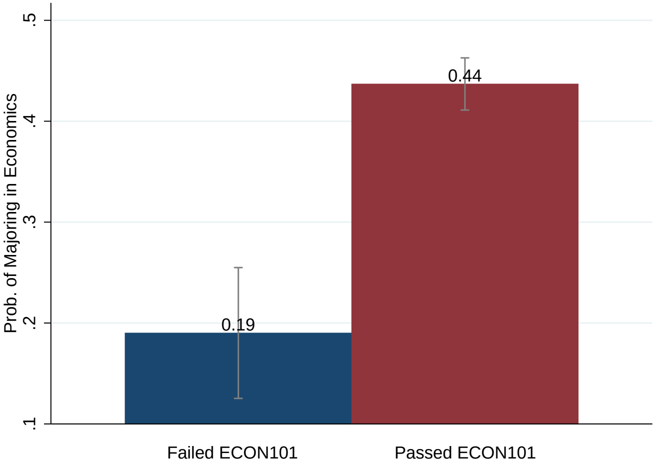
The Data: Graphs

Figure 5: Econ. Major by Professor



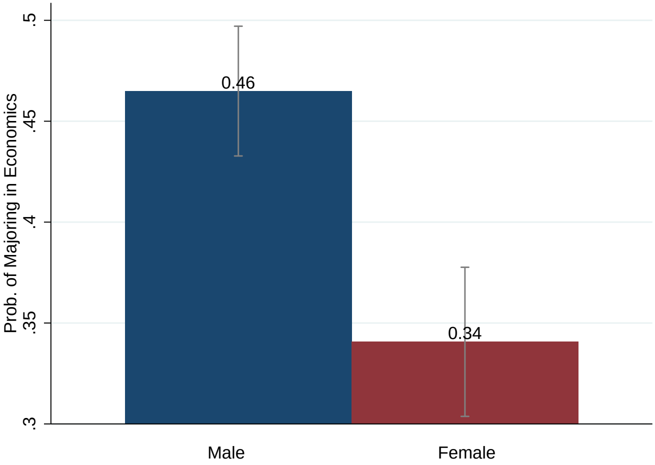
The Data: Graphs

Figure 6: Econ. Major by ECON101 Outcome



The Data: Graphs

Figure 7: Econ. Major by Gender



Results

The results of the estimated model are presented in Table 2.

Table 2: Probit Estimates (Marginal Effects)

	(1) Econ. Major		(2) Econ. Major		(3) Econ. Major		(4) Econ. Major	
Prof. 2 (d)	0.0912	(0.0897)	0.0252	(0.0815)	0.0188	(0.0751)	0.0191	(0.0749)
Prof. 3 (d)	0.0742	(0.120)	0.0634	(0.154)	0.0581	(0.149)	0.0583	(0.148)
Prof. 4 (d)	0.0328	(0.0860)	0.0565	(0.105)	0.0836	(0.0999)	0.0841	(0.1000)
Prof. 5 (d)	0.0186	(0.0813)	0.0351	(0.101)	0.0619	(0.0959)	0.0623	(0.0955)
Prof. 6 (d)	0.152	(0.136)	0.129	(0.148)	0.132	(0.140)	0.132	(0.140)
Prof. 7 (d)	0.0629	(0.0925)	0.0519	(0.101)	0.0853	(0.0931)	0.0856	(0.0926)
Prof. 8 (d)	0.136	(0.0874)	0.123	(0.112)	0.124	(0.107)	0.123	(0.105)
Prof. 9 (d)	0.220**	(0.0994)	0.214**	(0.107)	0.214**	(0.101)	0.215**	(0.101)
Prof. 10 (d)	0.160*	(0.0887)	0.153*	(0.0931)	0.154*	(0.0879)	0.154*	(0.0884)
Prof. 11 (d)	0.142**	(0.0716)	0.161*	(0.0875)	0.168**	(0.0819)	0.168**	(0.0824)
Prof. 12 (d)	0.105	(0.0863)	0.132	(0.113)	0.120	(0.109)	0.120	(0.108)
Prof. 13 (d)	0.223*	(0.123)	0.228*	(0.126)	0.215	(0.131)	0.215	(0.131)
Failed (d)					-0.236***	(0.0433)	-0.236***	(0.0439)
School GPA							0.00258	(0.0374)
Blocks	NO		YES		YES		YES	
Obs.	1561		1561		1561		1559	

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Characteristics and Major Choice

Students evaluate their teachers every semester in twelve areas (see Table 6) with a discrete score that spans from 1 to 7.

Table 5: Teacher Evaluation Survey

Q	Characteristic (in Spanish)
01.	Demuestra seguridad y dominio sobre las materias
02.	Prepara las clases
03.	Es claro para exponer las materias
04.	Resuelve dudas y problemas de los alumnos
05.	Incentiva la discusión y participación
06.	Permite hacer preguntas y expresar ideas
07.	Estimula el interés por las materias
08.	Hace evaluaciones justas y razonables
09.	Asiste puntualmente a clases
10.	Cumple plazos y normas establecidas
11.	Trata a sus alumnos con respeto
12.	Está disponible para sus alumnos

Characteristics and Major Choice

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Table 6: (Translated) Teacher Evaluation Survey

Q	Characteristic
01.	Shows confidence regarding the subject
02.	Prepares classes
03.	Exposes the subject clearly
04.	Solves doubts and problems for students
05.	Promotes discussion and participation
06.	Allows asking questions and sharing ideas
07.	Stimulates interest for the subject
08.	Evaluates justly and fairly
09.	Shows up punctually to class
10.	Meets deadlines and established norms
11.	Treats students respectfully
12.	Is available for students

Characteristics and Major Choice

In this way, I can estimate the effect of each of these characteristics with the reduced-form probit model described by

$$Y_i = \beta_0 + \sum_{j \in J} T_{ij} \cdot \left(\sum_{k \in K} \beta_k Q_{ijk} \right) + \mathbf{XB} + \varepsilon_i, \tag{4}$$

where Q_{ijk} denotes the score for teacher j in characteristic $k \in K$.

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where Q_{ijk} denotes the score for teacher j in characteristic $k \in K$.

But Q_{ijk} is endogenous!

Indeed, so we replace it by Q_{tjk}, i.e. the average score of characteristic k for professor j in cohort t (excluding student i).

Results

Table 7: Effect of Teacher Characteristics on Major

	(1) Econ. Major		(2) Econ. Major		(3) Econ. Major		(4) Econ. Major	
Q1	0.0437	(0.104)	0.00895	(0.114)	0.000703	(0.113)	0.00102	(0.114)
Q2	0.0168	(0.0469)	-0.00517	(0.0530)	0.0124	(0.0568)	0.00607	(0.0585)
Q3	-0.0523	(0.0870)	0.0175	(0.0989)	0.0335	(0.105)	0.0324	(0.105)
Q4	-0.0998	(0.157)	-0.101	(0.187)	-0.103	(0.188)	-0.107	(0.187)
Q5	-0.0495	(0.0649)	-0.0452	(0.0620)	-0.0387	(0.0620)	-0.0403	(0.0619)
Q6	0.163*	(0.0930)	0.153	(0.0981)	0.178**	(0.0898)	0.182**	(0.0920)
Q7	0.0982	(0.0766)	0.0736	(0.0868)	0.0456	(0.0907)	0.0447	(0.0908)
Q8	0.143***	(0.0377)	0.126***	(0.0441)	0.0985**	(0.0415)	0.102**	(0.0408)
Q9	-0.0716	(0.0535)	-0.0725	(0.0477)	-0.0707	(0.0477)	-0.0690	(0.0465)
Q10	0.0349	(0.0404)	0.0527	(0.0380)	0.0634*	(0.0383)	0.0641*	(0.0386)
Q11	-0.178***	(0.0459)	-0.170***	(0.0578)	-0.172***	(0.0559)	-0.170***	(0.0548)
Q12	-0.00606	(0.0678)	-0.00322	(0.0764)	-0.0176	(0.0770)	-0.0151	(0.0782)
Failed (d)					-0.238***	(0.0380)	-0.236***	(0.0385)
School GPA							0.00828	(0.0358)
Blocks	NO		YES		YES		YES	
Obs.	1540		1540		1540		1539	

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

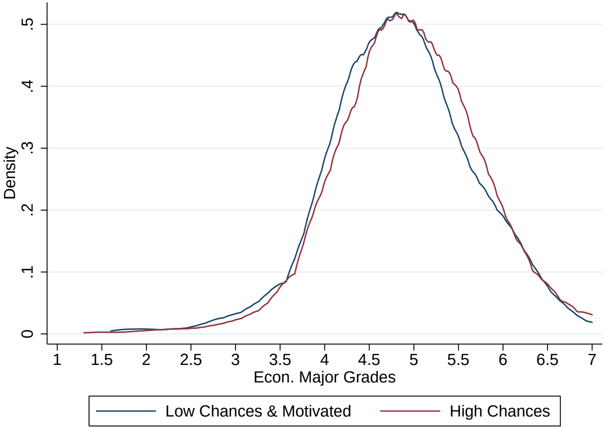
Negative Sorting?

Some may be worried about the implications of these exogenous shocks: “perhaps some students that *should not* major in economics are motivated to do so, and therefore under-perform”.

Negative Sorting?

Some may be worried about the implications of these exogenous shocks: "perhaps some students that *should not* major in economics are motivated to do so, and therefore under-perform". Nope:

Figure 8: Under-Median but Motivated vs. Over-Median Econ. Major GPA



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- Certain particular characteristics make students more prone to choosing on major over another.
- High internal validity.
- Lack of external validity.
- Future agenda: i) relative, not absolute measures of teachers and ii) effects on labor maker outcomes.

References I

Angrist, Joshua D. and Jörn-Steffen Pischke (2008). Mostly Harmless Econometrics: An Empiricist's Companion. Princeton University Press.

Arcidiacono, Peter (2004). Ability sorting and the returns to college major. In: Journal of Econometrics 121.1-2. Higher education (Annals issue), pp. 343–375.

Arcidiacono, Peter, V. Joseph Hotz, and Songman Kang (2012). Modeling college major choices using elicited measures of expectations and counterfactuals. In: Journal of Econometrics 166.1. Annals Issue on "Identification and Decisions", in Honor of Chuck Manski's 60th Birthday, pp. 3–16.

Carrell, Scott E. and James E. West (2010). Does Professor Quality Matter? Evidence from Random Assignment of Students to Professors. In: Journal of Political Economy 118.3, pp. 409–432.

Chambliss, Daniel F. and Christopher G. Takacs (2014). How college works. Harvard University Press.

Cho, Donghun, Wonyoung Baek, and Joonmo Cho (2015). Why do good performing students highly rate their instructors? Evidence from a natural experiment. In: Economics of Education Review 49, pp. 172–179.

Dee, Thomas S. (Feb. 1, 2004). Teachers, Race, and Student Achievement in a Randomized Experiment. In: Review of Economics and Statistics 86.1, pp. 195–210.

Duflo, Esther, Rachel Glennerster, and Michael Kremer (2007). Using Randomization in Development Economics Research: A Toolkit. In: Handbook of Development Economics. Ed. by T. Paul Schultz and John A. Strauss. Vol. 4. Elsevier, pp. 3895–3962.

References II

Glennerster, Rachel and Kudzai Takavarasha (2013). Running Randomized Evaluations: A Practical Guide. Princeton University Press.

Hastings, Justine, Christopher A. Neilson, and Seth D. Zimmerman (June 2015). The Effects of Earnings Disclosure on College Enrollment Decisions. Working Paper 21300. National Bureau of Economic Research.

Holland, Paul W. (1986). Statistics and Causal Inference. In: Journal of the American Statistical Associati 81.396, pp. 945–960.

Imai, Kosuke and Marc Ratkovic (Mar. 2013). Estimating treatment effect heterogeneity in randomized program evaluation. In: The Annals of Applied Statistics 7.1, pp. 443–470.

Imbens, Guido W. and Donald B. Rubin (2015). Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction. New York, NY, USA: Cambridge University Press.

Imbens, Guido W. and Jeffrey M. Wooldridge (Mar. 2009). Recent Developments in the Econometrics of Program Evaluation. In: Journal of Economic Literature 47.1, pp. 5–86.

Karnani, Mohit (2016). Freshmen Teachers and College Major Choice: Evidence from a Random Assignment in Chile. Tech. rep. The American Economic Association's Registry for Randomized Controlled Trials.

Keane, Michael P. (2010). Structural vs. atheoretic approaches to econometrics. In: Journal of Econometric 156.1. Structural Models of Optimization Behavior in Labor, Aging, and Health, pp. 3–20.

Lehmann, Erich L. and Joseph P. Romano (Aug. 26, 2008). Testing Statistical Hypotheses. 3rd edition. New York: Springer. 786 pp.

References III

Montmarquette, Claude, Kathy Cannings, and Sophie Mahseredjian (2002). How do young people choose college majors? In: Economics of Education Review 21.6, pp. 543–556.

Rivkin, Steven G., Eric A. Hanushek, and John F. Kain (2005). Teachers, Schools, and Academic Achievement. In: Econometrica 73.2, pp. 417–458.

Rubin, Donald B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. In: Journal of Educational Psychology 66.5, pp. 688–701.

— (1977). Assignment to Treatment Group on the Basis of a Covariate. In: Journal of Educational and Bel 2.1, pp. 1–26.

Sacerdote, Bruce (2001). Peer Effects with Random Assignment: Results for Dartmouth Roommates. In: The Quarterly Journal of Economics 116.2, pp. 681–704.

Sohn, Hosung (2016). Mean and distributional impact of single-sex high schools on students' cognitive achievement, major choice, and test-taking behavior: Evidence from a random assignment policy in Seoul, Korea. In: Economics of Education Review, pp. -.

Wong, Justin A. et al. (2011). Essays on the Determinants of Student Choices and Educational Outcomes. Stanford University.

Zafar, Basit (2013). College Major Choice and the Gender Gap. In: Journal of Human Resources 48.3, pp. 545–595.

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