

Decoding Choices: The Role of Classroom Gender Composition in Post-Secondary Preferences

Seminar in Economics

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Contents

- 1 Brief overview
- 2 Mechanism and contribution
- 3 Data
- 4 Conceptual framework
- 5 Results
- 6 Heterogenities
 - Fields of Study Preferred by Female Students
 - Fields of Study Less Preferred by Female Students
 - Fields with Similar Preferences Between Genders

This paper.

Question: Does the gender composition within classrooms "influence" the post-secondary schooling decision?

Motivation: The decision regarding post-secondary studies carries profound implications, extending beyond career preferences to enduring consequences, notably in terms of income differentials¹

How:

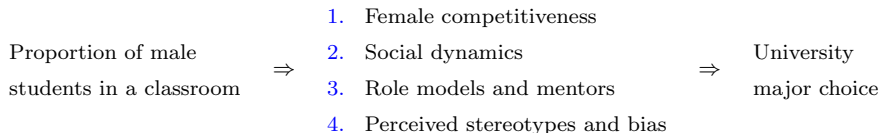
- ① Staggered DiD (Sun et al. 2020) estimation to identify the causal effect of transition from ex-female school to coeducational on schooling decision.
 - i. **Schooling Decision:** ↑ Do not pursue any study, ↓ Participation in STEM.
- ② Logistic regression model with fixed effects to identify the odd ratio of female students participating in STEM. As the male composition increases then:
 - i. **Schooling Decision:** ↑ O.R. Do not pursue any study, ↓ O.R. Participation in STEM.
- ③ Heterogenities
 - i. We examine 8 fields of study, and separately, we evaluate medicine and law

¹See, for example, Alesina, Giuliano, and Nunn (2013); Clifford D. Evans (2006); Evans and Diekmann (2009);

Importance of STEM Careers

- Between 2000-2003, 95% of US patents were related to the STEM field. (Rothwell 2013)
- As of 2011, 26 million U.S. jobs—20 percent of all jobs—require a high level of Study in any one STEM field. (Rothwell 2013)
- As of 2020, The direct STEM share of the economy of the US was 39.9% (FTI Consulting 2020)
- STEM fields are crucial for innovation, technology development, and economic growth.
- Countries with strong STEM workforces tend to be global leaders in research, new technologies, and high value-added industries.
- Each additional STEM job creates an extra 4-5 new jobs in the overall economy.

Mechanism: Factors Influencing Preferences



1. High school being a critical period for STEM career choices can be linked to competitiveness, especially for girls in traditionally male-dominated fields (Buser, Niederle, and Oosterbeek (2014); Sadler et al., 2012; Mann et al., 2013; Mann et al., 2015; Mann Legewie, 2015; Olitsky, 2014; Delaney Devereux, 2019).
2. The social environment and their previous education in STEM fields can be a powerful social influence. (Pregaldini et al., 2020; Bottia et al., 2015; Shvetsova et al., 2020; Mael et al., 2005; Patterson Pahlke, 2011; Opie et al., 2019;).
3. Lack of female role models in STEM fields might be a contributing factor. (Giustinelli and Manski (2018); Valbuena (2011);).
4. The way schools are structured and societal norms can discourage girls from pursuing STEM careers. (Collard & Stalker, 1991; Crosby, 1994; Wang & Degol, 2013; Tyler-Wood et al., 2018).

Contribution: This paper studies how...

- Unlike prior studies that focus on social dynamics in general (e.g., Pregaldini et al., 2020; Shvetsova et al., 2020), this research isolates the influence of a **higher proportion of male students** in the classroom on girls' university major choices, particularly in STEM fields.
- Despite similarities to works examining classroom gender composition and STEM performance (e.g., Sadler et al., 2012; Bottia et al., 2015), this study directly evaluates the impact on **university major selection**, a more specific indicator of career path.
- The finding that a higher proportion of boys narrows the gender gap in STEM majors adds a new dimension to existing research. It highlights the **complex interplay between social dynamics and student choice** in STEM fields, which wasn't previously explored in detail (e.g., OECD. (2017). PISA 2015; Eisenkopf, Hessami, Fischbacher, and Ursprung (2015)).

Data

The data used for the develop of this research are:

- Student Enrollment System (SIMAT) from 2012 to 2019. (Restricted Access)
- National Higher Education Information System (SNIES) 2012-2021. (Restricted Access)
- DANE - Formal Education (EDUC) 2010-2020. (Open and Public)

Distribution of Proportion of Males in Class Groups

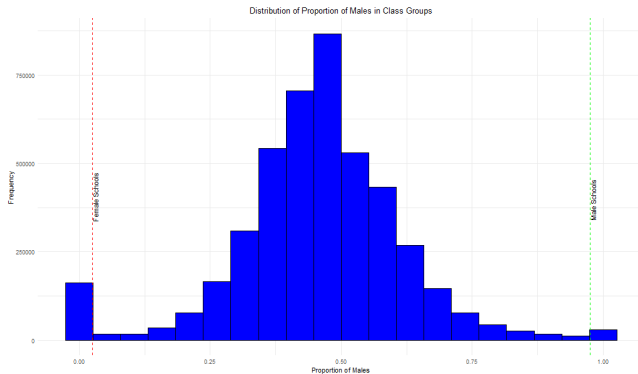


Figure: Distribution of Proportion of Males in Class Groups

Distribution by Gender according to the Field of Study

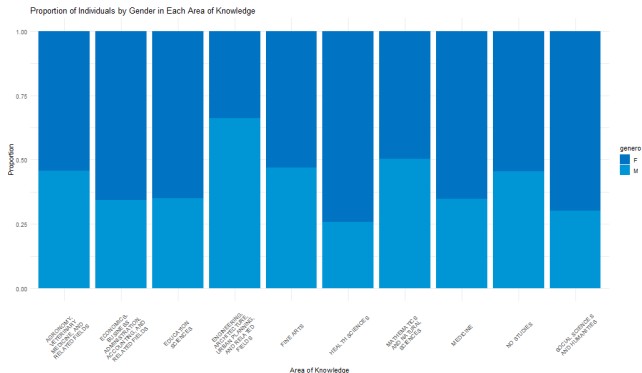


Figure: Distribution by Gender according to the Field of Study

Model Specification

$$\log \left(\frac{P(Y_{i,s,t}^c = 1)}{1 - P(Y_{i,s,t}^c = 1)} \right) = \beta_1 \times Gender_{i,s,t} + \beta_2 \times X_{i,s,t}^c + \gamma_t + \gamma_s + \varepsilon_{i,s,t} \quad (1)$$

Where:

- $Y_{i,s,t}^c$: Binary response variable for student i who completed secondary school in school s , choosing university major c .
- $Gender_{i,s,t}$: Indicator for female students.
- $X_{i,s,t}^c$: Vector of student characteristics.
- γ_t : Year fixed effects.
- γ_s : School fixed effects.
- $\varepsilon_{i,s,t}$: Error term.

► [Jump to BCE](#)

Staggered Difference-in-Differences (S-DiD) Design

To address potential biases intrinsic to fixed effect estimation, we employ a distinct approach by leveraging the transition from single-sex schools to co-educational settings.

$$\hat{\tau} = \text{Participation}_{\text{after transition}}^{\bar{P}} - \text{Participation}_{\text{before transition}}^{\bar{P}} \quad (2)$$

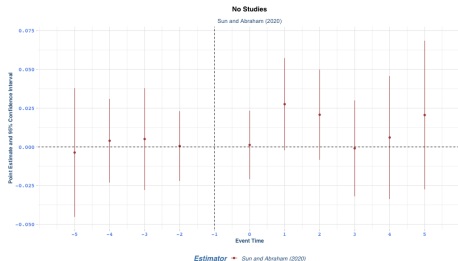
$$\text{Participation}_{c,t,j}^P = \beta_0 + \sum_{\varphi=-S}^{-2} \mu_{\varphi} \cdot D_{c,\varphi} + \sum_{\varphi=0}^M \mu_{\varphi} \cdot D_{c,\varphi} + \sigma_t + \gamma_c + \varepsilon_{c,t} \quad (3)$$

2

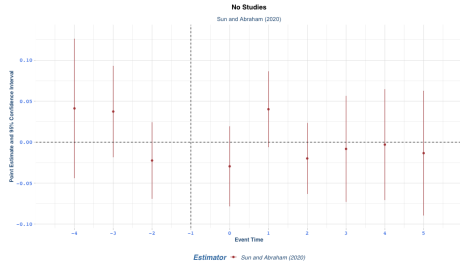
²Here $\text{Participation}_{c,t,j}^P$ represents the level of participation of students in major P at a particular school c and time t . β_0 is the intercept or baseline level of participation in major P . μ_{φ} are the parameters associated with the different time periods or treatment phases (φ). $D_{c,\varphi}$ are dummy variables denoting the treatment status (e.g., before and after the transition) for school c at time φ . σ_t captures time-specific effects. γ_c captures school-specific effects. $\varepsilon_{c,t}$ is the error term.

Changes in Proportion of Students Not Pursuing Further Studies

Changes in the Proportion of Students That Not Pursue Further Studies in Schools Transitioning from Single-Sex to Coeducational



Ex female schools



Ex male schools

Likelihood of Not Pursuing Further Studies

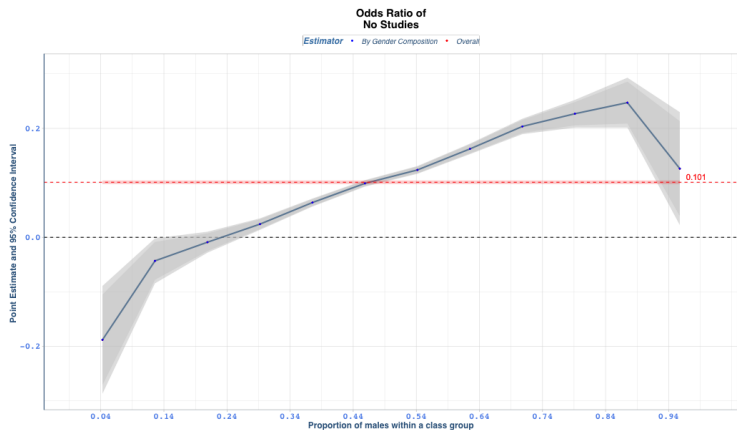
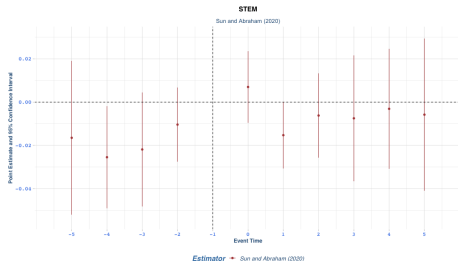


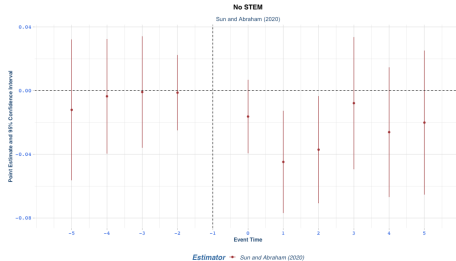
Figure: Likelihood of a female student choosing not to pursue further studies

Changes in Proportion of Students Choosing STEM

Changes in the Proportion of Students Choosing STEM Majors in Schools Transitioning from Single-Sex to Coeducational



Ex female schools



Ex female schools

Likelihood of a female student choosing STEM

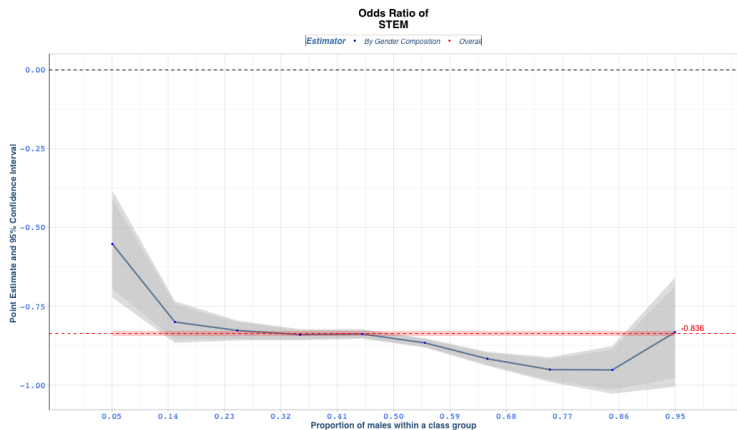


Figure: Likelihood of a female student choosing not to pursue further studies

Conclusion

- Our study highlights how classroom gender composition influences university major decisions.
- More male students led to increased interest for female students in traditionally male-dominated fields like engineering, architecture, and mathematics.
- More male students in a classroom led to increased interest in humanities, social sciences, education science, etc.
- Minimal gender differences are observed in agriculture, veterinary sciences, and medicine, suggesting limited influence of classroom gender compositions in these domains.

Decoding Choices: The Role of Classroom Gender Composition in Post-Secondary Preferences

9th LEER Conference on Education Economics

Thank You!

Jaime Polanco-Jiménez³

Kristof De Witte⁴

Gloria L. Bernal⁵

April 10, 2024

Fields of Study Preferred by Female Students

Economics, Business and Related Majors

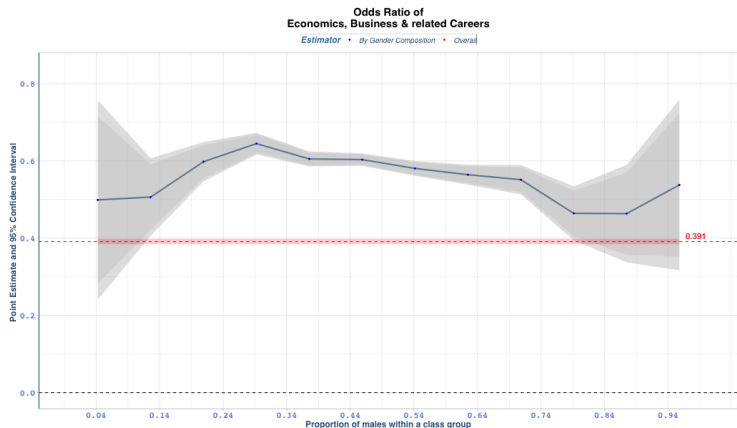


Figure: Likelihood of a female student choosing economics/business-related majors

Fields of Study Preferred by Female Students

Social Sciences/Humanities Majors

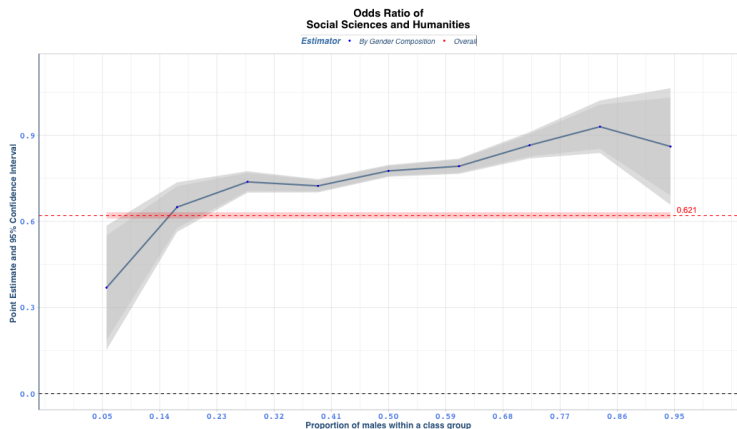


Figure: Likelihood of a female student choosing social sciences/humanities majors

Fields of Study Preferred by Female Students

Education Sciences Majors

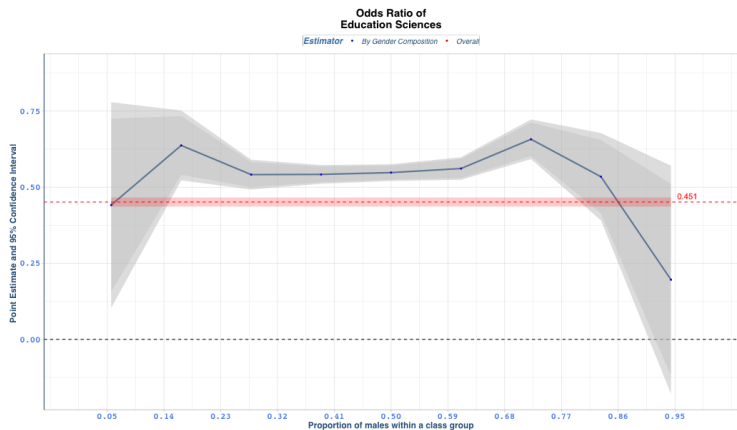


Figure: Likelihood of a female student choosing education sciences majors

Fields of Study Preferred by Female Students

Health Sciences Majors (Except Medicine)

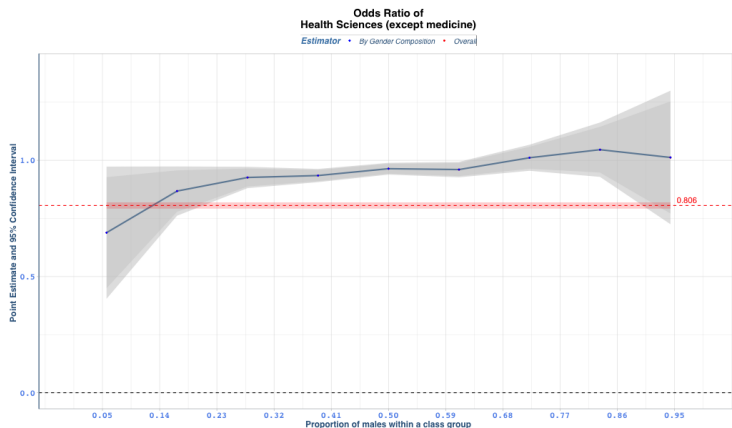


Figure: Likelihood of a female student choosing health sciences majors

Fields of Study Preferred by Female Students

Medicine Major

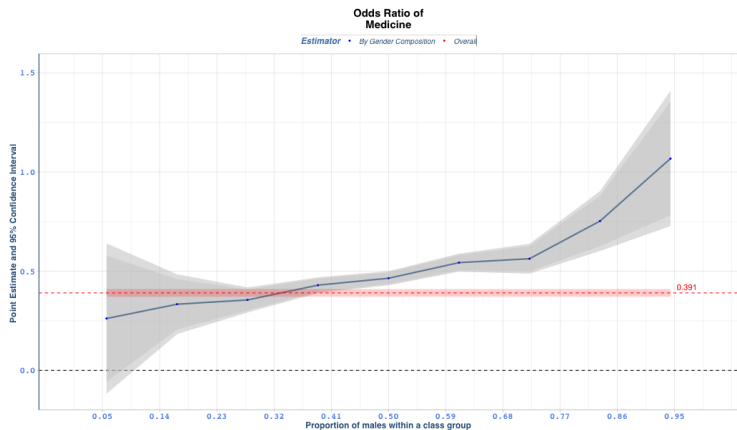


Figure: Likelihood of a female student choosing medicine majors

Fields of Study Preferred by Female Students

Law Major

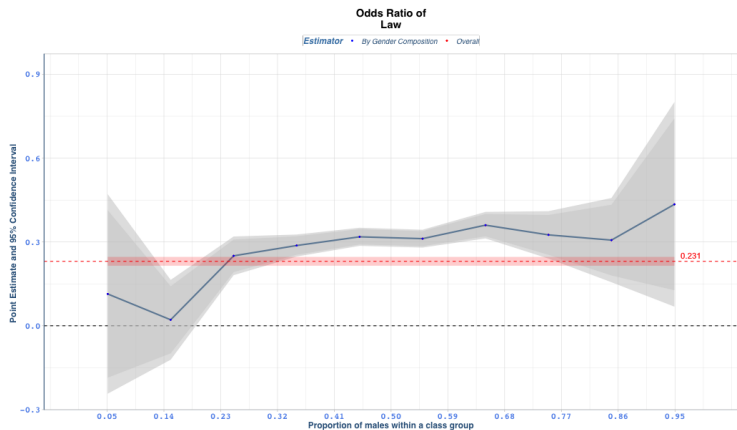
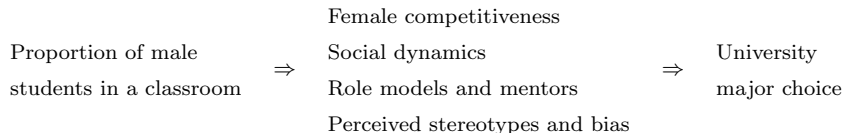


Figure: Likelihood of a female student choosing law majors

Factors Influencing Preferences



- Fields of Study Preferred by Female Students [▶ Jump to Results](#)
- Fields of Study Less Preferred by Female Students [▶ Jump to Results](#)
- Fields with Similar Preferences Between Genders [▶ Jump to Results](#)

Fields of Study Less Preferred by Female Students

Engineering/Architecture Related Majors

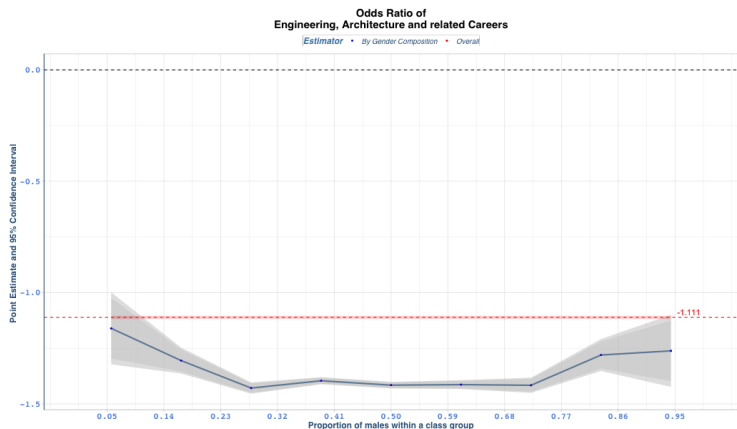


Figure: Likelihood of a female student choosing engineering/architecture-related majors

Fields of Study Less Preferred by Female Students

Mathematics and Natural Sciences Majors

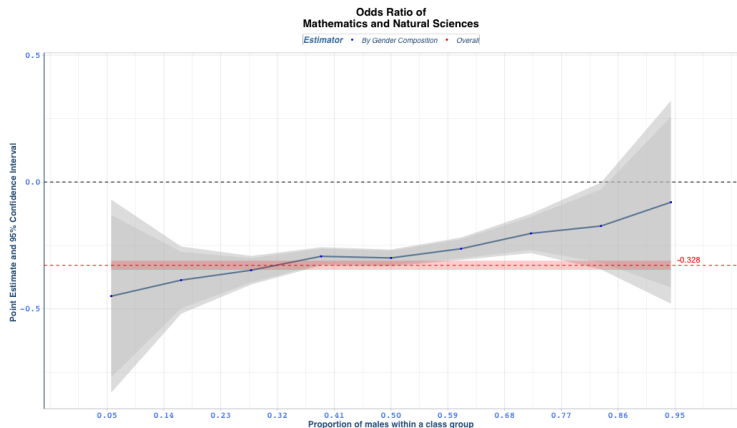
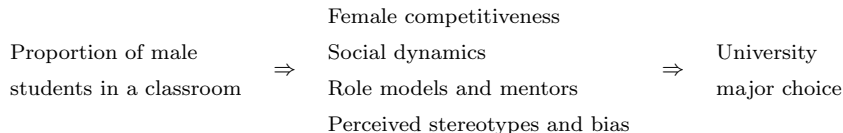


Figure: Likelihood of a female student choosing mathematics/natural sciences majors

Factors Influencing Preferences



- Fields of Study Preferred by Female Students [▶ Jump to Results](#)
- Fields of Study Less Preferred by Female Students [▶ Jump to Results](#)
- Fields with Similar Preferences Between Genders [▶ Jump to Results](#)

Fields with Similar Preferences Between Genders

Fine Arts Majors

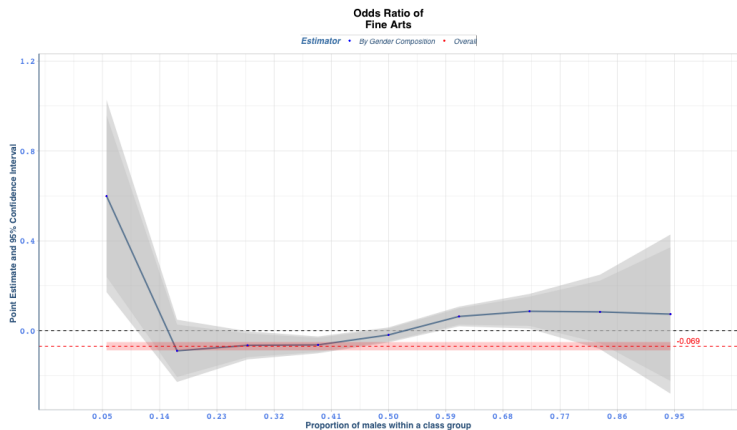


Figure: Likelihood of a female student choosing fine arts majors

Fields with Similar Preferences Between Genders

Agronomy/Veterinary Related Majors

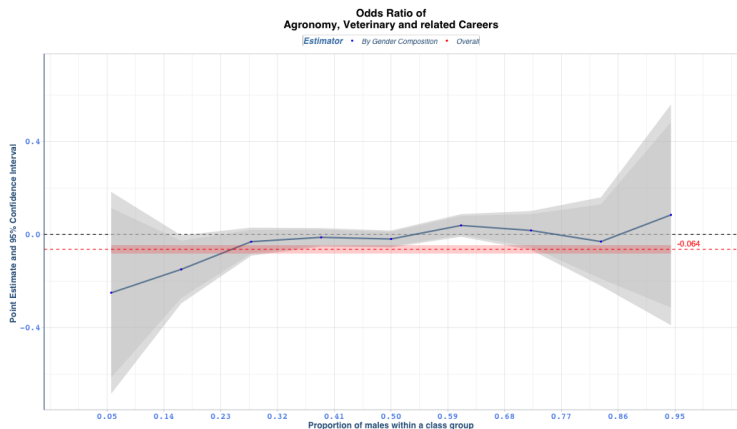


Figure: Likelihood of a female student choosing agronomy/veterinary-related majors

Optimal Bandwidth Estimation based on Binary Cross-entropy

In order to analyze the probability that a secondary school student chooses an Field of Study P to pursue post-secondary studies, we examine the probability according to different gender compositions in the classrooms. Therefore, we assume that there exists a fixed value that allows us to subset by $\exists X_{\text{optimal}}$.

The formal representation using mathematical notation for the partitioning of the range into fixed intervals:

$$\begin{aligned}X_1 &= [0, X_{\text{optimal}}) \\X_2 &= [X_{\text{optimal}}, 2X_{\text{optimal}}) \\X_3 &= [2X_{\text{optimal}}, 3X_{\text{optimal}}) \\&\dots \\X_n &= [(n-1)X_{\text{optimal}}, nX_{\text{optimal}})\end{aligned}$$

These representations X_i cover the entire range in fixed intervals of X_{optimal} and define distinct subsets, each representing an interval of size X_{optimal} within the overall range. To estimate X_{optimal} , we modify the methodology proposed in Imbens and Kalyanaraman (2012). In it, the key step is to replace the mean squared error (MSE) criterion with a

Optimal Bandwidth Estimation based on Binary Cross-entropy

The key outcome we are trying to predict is a binary variable indicating whether a student chooses a particular Field of study (e.g. science, humanities, etc.) or not. Let's call this $Y_i \in \{0, 1\}$.

$Y_i = 1$ means student i chose that Field of study, and $Y_i = 0$ means they did not choose that Field. Our regression discontinuity model is estimating the probability $p_i = P(Y_i = 1|X_i)$ that the student chooses that Field, conditioned on the gender composition in classrooms X_i .

Let's call this estimated probability $m(X_i)$, which depends on the bandwidth h .

The BCE loss for a single data point measures how well our model is estimating this probability.

It is:

$$\text{BCE}_i = \begin{cases} -\log(m(X_i)), & \text{if } Y_i = 1 \\ -\log(1 - m(X_i)), & \text{if } Y_i = 0 \end{cases}$$

This penalizes underestimating probability if the actual outcome is 1 and penalizes overestimating probability if the actual outcome is 0. We then define the overall expected BCE loss over the distribution of (X_i, Y_i) as:

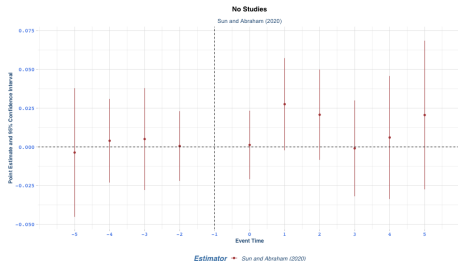
$$\text{BCE}(h) = E[-Y_i \log(m(X_i)) - (1 - Y_i) \log(1 - m(X_i))]$$

Minimizing this $\text{BCE}(h)$ gives the optimal bandwidth for our model.

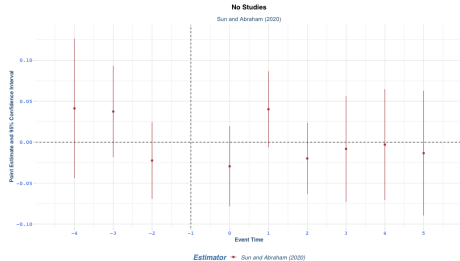
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Changes in Proportion of Students Not Pursuing Further Studies

Changes in the Proportion of Students That Not Pursue Further Studies in Schools Transitioning from Single-Sex to Coeducational



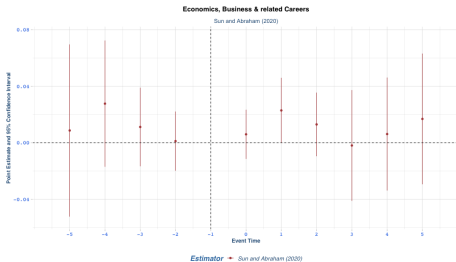
Ex female schools



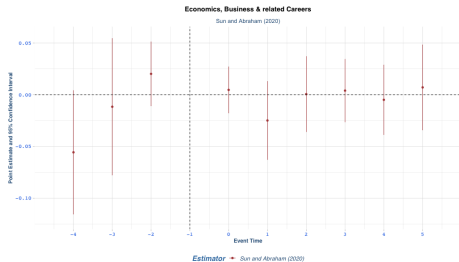
Ex male schools

Economics, Business and Related Majors:

Changes in the Proportion of Students Choosing Economics and Business Related Majors in Schools Transitioning from Single-Sex to Coeducational



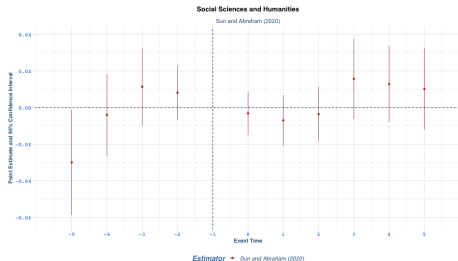
Ex female schools



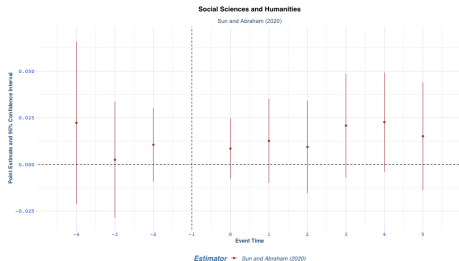
Ex male schools

Social Sciences/Humanities Majors:

Changes in the Proportion of Students Choosing Social Sciences in Schools Transitioning from Single-Sex to Coeducational



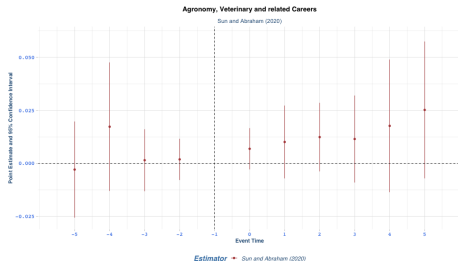
Ex female schools



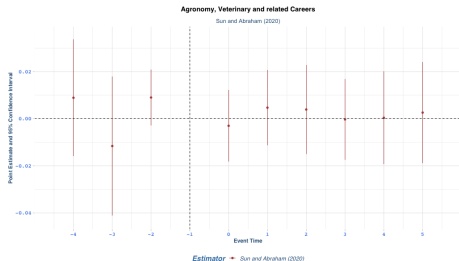
Ex male schools

Education Sciences Majors:

Changes in the Proportion of Students Choosing Education Sciences Majors in Schools Transitioning from Single-Sex to Coeducational



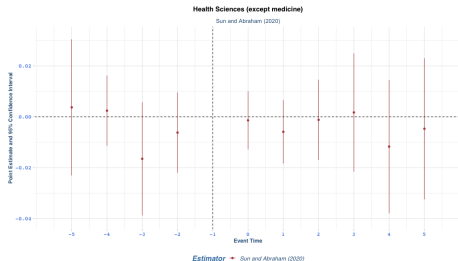
Ex female schools



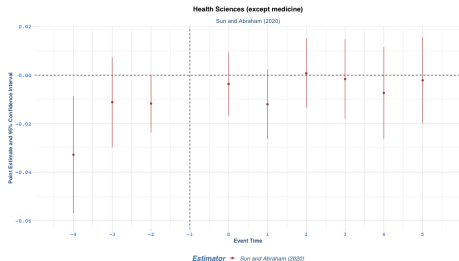
Ex male schools

Health Sciences Majors (Except Medicine):

Changes in the Proportion of Students Choosing Health Science Majors (Except Medicine)
in Schools Transitioning from Single-Sex to Coeducational



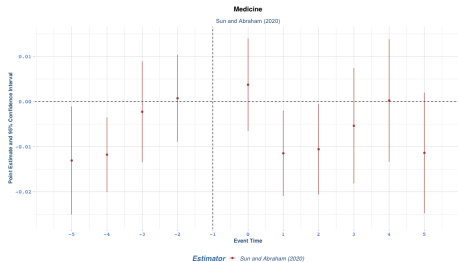
Ex female schools



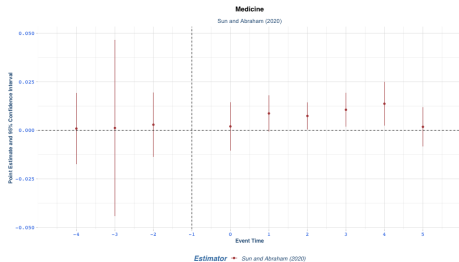
Ex male schools

Medicine Major:

Changes in the Proportion of Students Choosing A Major in Medicine from Schools Transitioning from Single-Sex to Coeducational



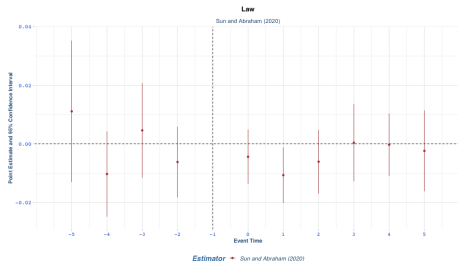
Ex female schools



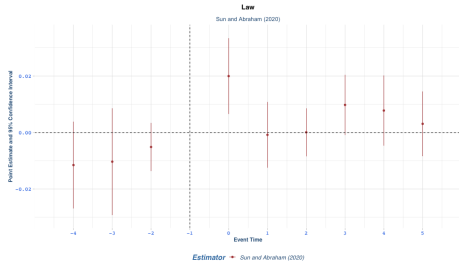
Ex male schools

Law Majors:

Changes in the Proportion of Students Choosing a Major in LAW in Schools Transitioning from Single-Sex to Coeducational



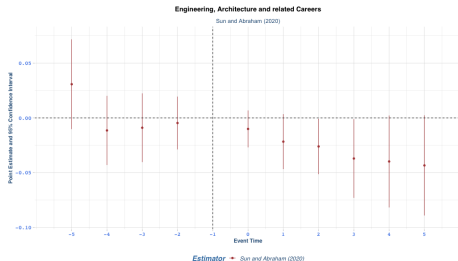
Ex female schools



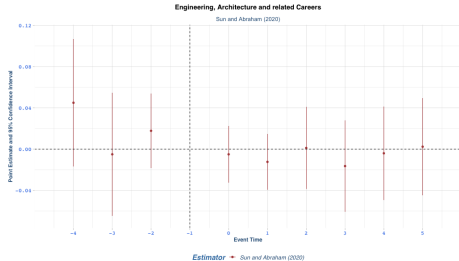
Ex male schools

Engineering/Architecture Related Majors:

Changes in the Proportion of Students Choosing Engineering, Architecture and Related Majors in Schools Transitioning from Single-Sex to Coeducational



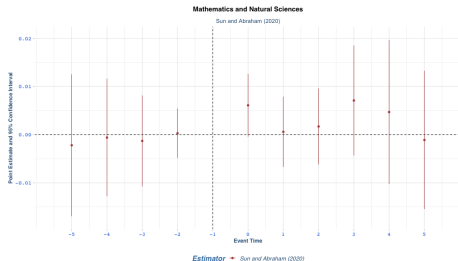
Ex female schools



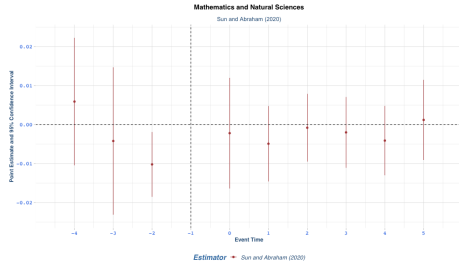
Ex male schools

Mathematics and Natural Sciences Majors:

Changes in the Proportion of Students Choosing Mathematics, Natural Sciences and Related Majors in Schools Transitioning from Single-Sex to Coeducational



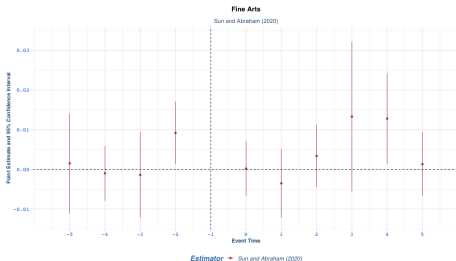
Ex female schools



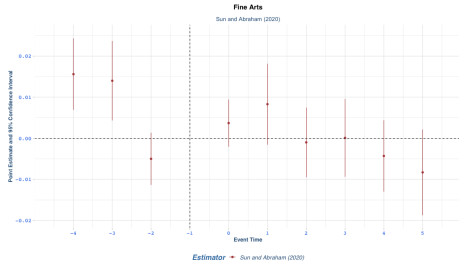
Ex male schools

Fine Arts Majors:

Changes in the Proportion of Students Choosing Fine Arts and Related Majors in Schools Transitioning from Single-Sex to Coeducational



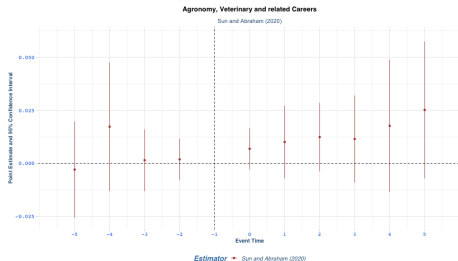
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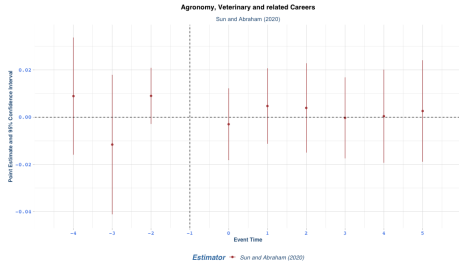
Ex male schools

Agronomy/Veterinary Related Majors:

Changes in the Proportion of Students Choosing Agronomy, Veterinary, and Related Majors in Schools Transitioning from Single-Sex to Coeducational



Ex female schools



Ex male schools

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