# Online Appendix for:
# College Major Choice, Payoffs, and Gender Gaps

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## Table of Contents

# A Data Appendix

This section discusses additional details regarding the data used in our analysis. We begin by providing details about our categorization of majors that are crucial in our analysis. Then, since earnings records are top-coded, we discuss our imputation procedure. We also report additional descriptive evidence related to trends in gender representation, preferences, and standardized test scores mentioned in the paper.

## A.1 Major Classification

We classify students into fields of study based on the major from which they graduate. Degree programs are classified by field of study mostly based on the OECD Handbook for Internationally Comparative Education Statistics (OECD, 2004). There are eight broad categories: "*Agriculture*", "*Science*", "*Social Sciences, Business and Law*", "*Teaching*", "*Humanities and Arts*", "*Engineering, Manufacturing and Construction*", "*Health and Welfare*", and "*Services*".

We reclassify the category "*Social Sciences, Business and Law*" into three separate fields of study "*Social Sciences*", "*Business*", and "*Law*". The field of "*Social Sciences*" includes the degrees of anthropology, library science, political sciences, social communication, geography, journalism, psychology, sociology, and social work. The field of "*Business*" includes the degrees: commercial engineering, accounting, commerce engineering, business administration, marketing engineering, logistics engineering, foreign trade engineering, management control engineering, human resources engineering, finance engineering, public management, advertising, and public relations; while the field of "*Law*" includes law degrees.

We also separate "*Medicine*" from "*Health and Welfare*". In particular, we include all degrees covered by the "Medical Law" in Chile (Ley N 19,664) into "*Medicine*". These degrees are in medicine, dentistry, pharmaceutical chemistry, and biochemistry. Finally, we drop "*Agriculture*" and "*Services*" as they represent very few graduates (less than 5%) from non-homogeneous college programs in Chile.

## A.2 Data Imputations

To impute wages above the social security contribution limit, we proceed as in Dustmann et al. (2009) and Card et al. (2013). First, we fit a series of Tobit models to log wages separately by gender, including the type of high school, test-score range, and region controls.

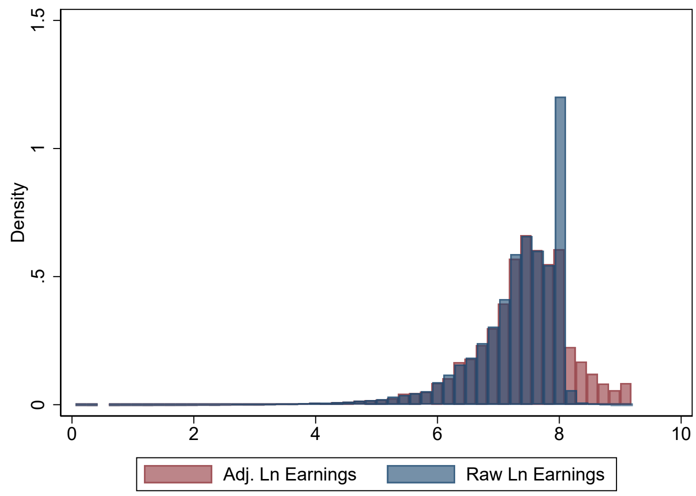
Then, we impute an uncensored value for each censored observation using the estimated parameters of these models and random drawings $\epsilon$ from a truncated distribution.

Following Gartner et al. (2005):

$$\epsilon_i = \Phi^{-1}\left(u \times \left[1 - \Phi\left(\frac{c - X_i'\hat{\beta}}{\hat{\sigma}}\right)\right] + \Phi\left(\frac{c - X_i'\hat{\beta}}{\hat{\sigma}}\right)\right),$$

where $u \sim$ U[0,1], $c$ is the social security contribution limit, $X'\hat{\beta}$ is the Tobit prediction, and $\hat{\sigma}$ is the standard deviation of the Tobit error. Figure A.1 below presents both the distribution of the original log earnings and the imputation-adjusted log earnings used in our analysis.

Figure A.1: Log Earnings Distribution




Notes: This figure presents the histogram of the original log earnings and the imputation-adjusted log earnings. We adjust earnings at the contribution limit following Dustmann et al. (2009) and Card et al. (2013). For details, see section A.2.

## A.3 Descriptive Evidence

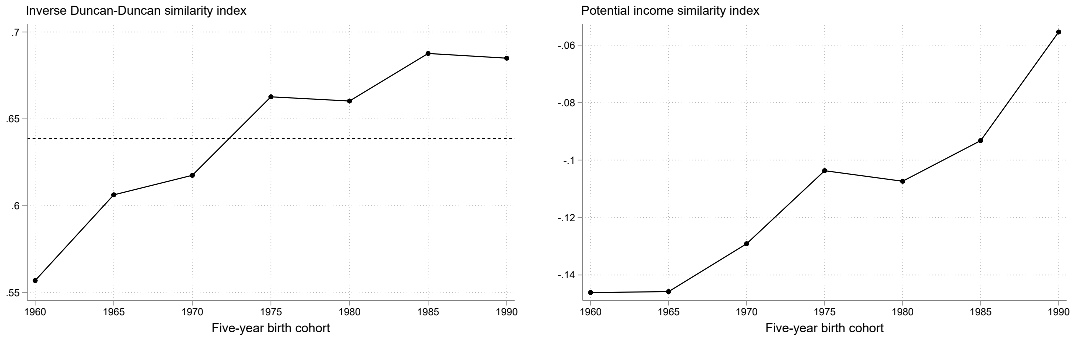
We present descriptive evidence that motivates and complements our work.

**Historical Trends:** Figure A.2 documents trends in gender representation across majors and its potential contribution to the overall gender gap. In the spirit of Sloane et al. (2021), and leveraging the largest household survey in Chile, the figure shows the major "similarity index" (as a re- normalization of the inverse Duncan-Duncan index) and a "potential wage index" (that assigns to everyone within a major the average hourly wages of prime-age male workers in that major). This figure shows that majors in Chile have become less segregated over time. See section 2 for details.

**Fields of Study:** To characterize preferences for fields of study, Figure A.3 reports fallback major prevalence. Overall, we find sensible patterns. For example, Social Science is the most common fallback option among students who rank Law programs as their most-preferred field, while Science is the most common fallback major for individuals who rank Engineering as their most-preferred field.

**Fertility:** Figure A.4 uses data from the World Bank World Development Indicators database and replicates the Figure presented in Doepke et al. (2023), including Chile. The figure shows total fertility rates since the seventies and highlights that Chile's fertility rates today are remarkably similar to those of high-income countries.

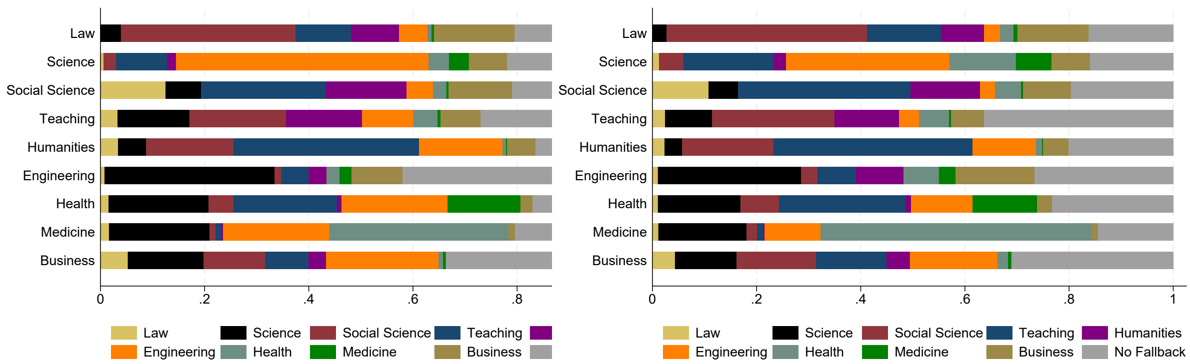
Figure A.2: Similarity and Potential Wage Indexes by Field of Study Across Cohorts




(a) Gender Similarity Index (b) Potential Wage Index

Notes: This figure presents trends in the similarity index and wage potential by field of study across cohorts, as in Sloane et al. (2021). Data comes from the largest household survey in Chile and is restricted to those with at least a bachelor's degree. Panel (a) plots the renormalized, inverse Duncan-Duncan index for different cohorts of Chilean college graduates. Panel (b) plots the potential wage index for different cohorts of Chilean college graduates.

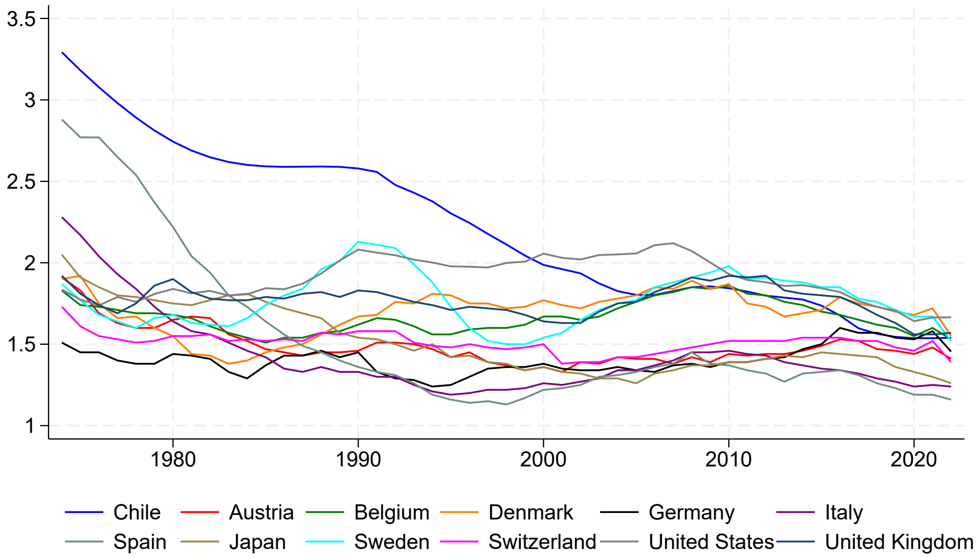
Figure A.3: Applicants' Fallbacks




(a) Male (b) Female

Notes: This figure shows students' fallback fields of study based on their ranked order lists. Among students ranking a given field as their first choice (y-axis), we compute the share of students ranking each of the remaining fields of study as a second option (i.e., fallback). Panels (a) and (b) show the relevance of each fallback for males and females, respectively. We consider all students who applied and were accepted through the centralized admission system between 2004 and 2007 and were employed in 2019.

Figure A.4: Total Fertility Rates Over Time




Notes: This figure shows the total fertility rates for the high-income countries considered in Doepke et al. (2023) and Chile (in blue). The data comes from the World Bank World Development Indicators database.

# B Supplementary Results

This section provides additional results mentioned in the paper. First, we provide evidence that our approach is consistent with that of Kirkeboen et al. (2016). Second, we show results on the dynamics of the gender earnings gap through the lens of a decomposition between differences in returns and differences in match effects. Finally, we discuss a set of additional results that all point to qualitatively similar conclusions as the main results in the paper.

## B.1 Relative Payoffs and Comparative Advantage:

Our findings complement and extend the evidence provided by Kirkeboen et al. (2016) on the importance of next-best alternatives and comparative advantage in the choice of college major.

Our approach resembles the fallback conditioning presented in Kirkeboen et al. (2016), as treatment effects vary according to the composition of a student's rank-ordered list, i.e., the payoff to a given field includes a match effect governed by the submitted rank-ordered list, including the fallback option and any subsequent fields a student ranks. This means that treatment effects for major $j$ differ for individuals with different fallbacks; and even among individuals with similar fallbacks, additional differences in the composition of the rank-ordered list produces additional differences in treatment effects. Table B.1

shows the fallback-specific returns estimated by our model. Results are consistent with those of Kirkeboen et al. (2016) in that payoffs are highly heterogeneous depending on each student's fallback. For instance, the payoff to Science go from positive for those with next best alternatives in Social Science, Teaching or Humanities to negative for those with next best alternatives in Business or Medicine.

## B.2 Additional Results

**Private Sector Earnings Data:** Appendix Table B.3 reports estimates using the private sector data discussed in Section 2. The overarching results are qualitatively similar to our main estimates. In this case, however, the return to Medicine is relatively smaller. This stems from the fact that many medical doctors are employed in the public sector in Chile, so estimates using private sector data will invariably miss a significant portion of their labor market. For this reason, we use the pension system records as our primary data.

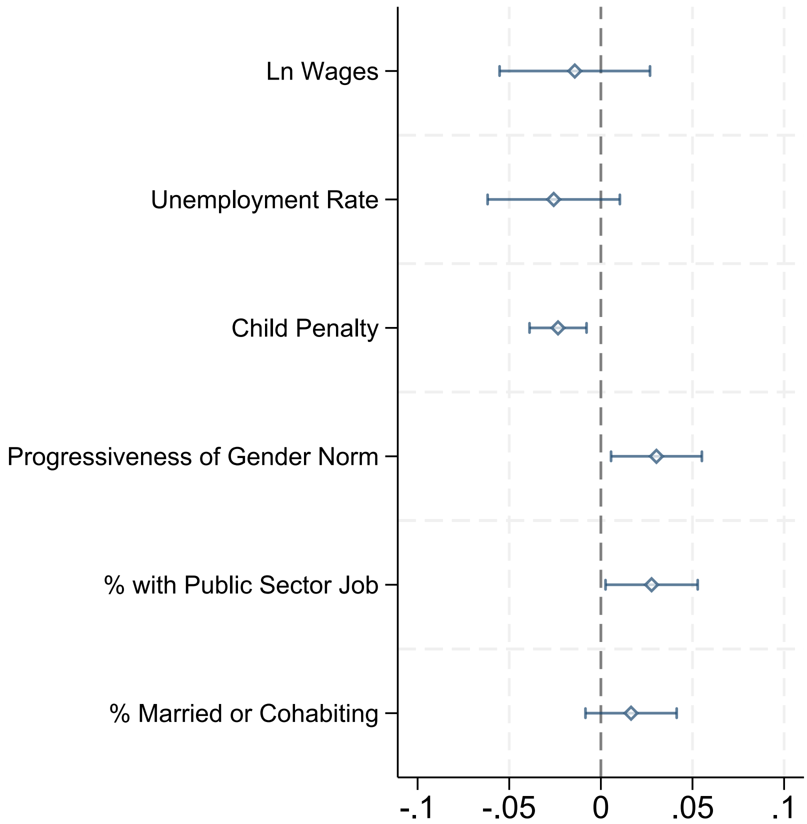
**Total Earnings:** Appendix Table B.2 reports estimates using the pension data but considering total yearly earnings instead of log earnings as the dependent variable. This allows us to include individuals not employed in the Chilean formal labor market in 2019. We find similar results when considering this outcome variable encompassing the intensive and extensive margins of the labor market. We find differences in returns across fields of study and gender. In line with our main results, men exhibit larger earnings in Science and Engineering, and women exhibit higher earnings in Teaching and Humanities, fields with relatively lower returns.

**Alternative Non-Pecuniary Returns:** The fertility results in the paper are on the extensive margin of having a child by a certain time after graduation. Appendix Table B.4 reports the estimates obtained when the outcome is the total number of children. This captures both extensive and intensive margin effects. Reassuringly, we find similar results when accounting for the intensive margin of fertility.

**Fertility Correlations:** We conjecture that majors impact fertility by allowing students to access jobs with different attributes and career opportunities. Our interpretation is consistent with the "new theories" underscoring that factors affecting the compatibility of women's careers and families are key drivers of fertility (Doepke et al., 2023). We present evidence supporting our hypothesis in Figure B.1, which reports the point estimates and confidence intervals obtained from separate regressions of fertility returns by field of study on job and field-specific attributes. For additional details, see Appendix C.

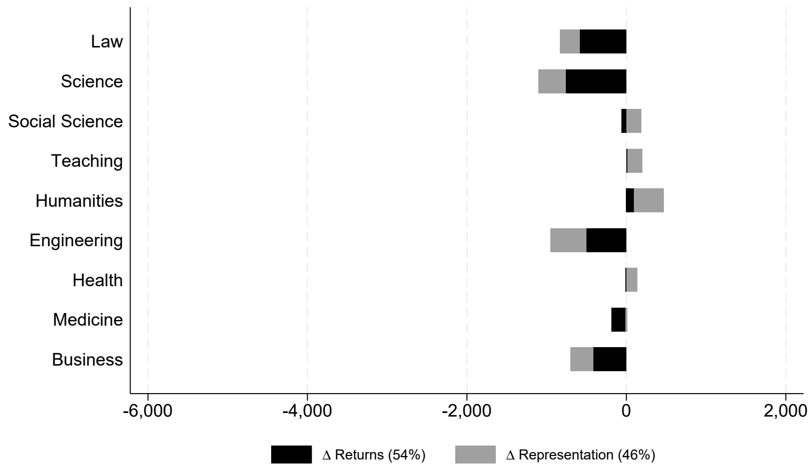
**Counterfactual Preferences:** Figure B.2 offers additional evidence on the impact of equalizing family considerations between genders. Based upon the decomposition presented in Equation (1), the Figure B.2 shows that equalizing preferences for family considerations significantly reduces the contribution of Engineering programs to the overall gender earnings gap while also diminishing the offsetting impact of Teaching and Health programs.

Figure B.1: Fertility Correlations

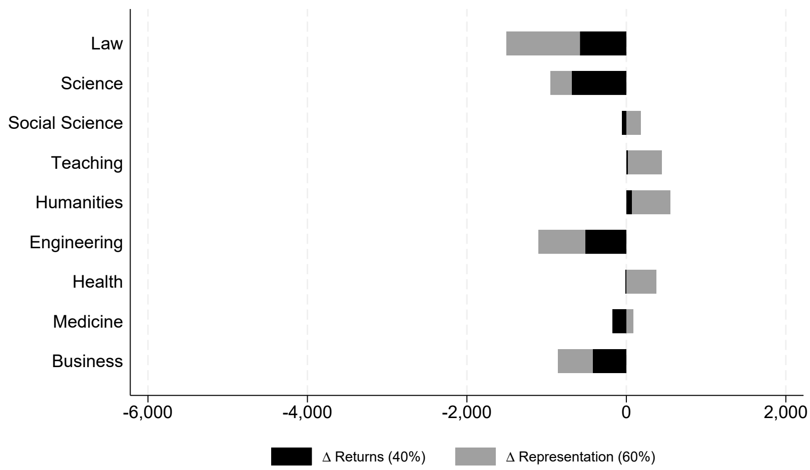



Notes: This figure reports the point estimates and confidence intervals obtained from separate regressions of fertility returns by field of study on job and field-specific attributes. All independent variables are standardized to have a mean of zero and a standard deviation of one. Confidence intervals are constructed using robust standard errors. For details on the construction of Child Penalties and Progressiveness of Gender Norm, see Appendix C.

Figure B.2: Baseline and Counterfactual Earnings Gap: Sorting versus Returns




(a) Baseline




(b) Counterfactual

Notes: These figures show the result from the exercise described by Equation (1) that decomposes the gender earnings gap into differences in sorting between fields of study and differences in returns within fields of study. We consider the annual earnings in 2019 of students who applied through the centralized admission system between 2004 and 2007, graduated between 2007 and 2019, and were employed in 2019. Panel (a) plots the results from the decomposition when we assign male preferences for family considerations to all students. Panel (b) plots the results from the decomposition when we assign female preferences for family considerations to all students. The predictions use estimates reported in Table 5, discussed in the main text.

Table B.1: Estimates of Relative Payoffs

| Completed field ($j$): | Next best alternative ($k$): | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Law | Science | Social Science | Teaching | Humanities | Engineering | Health | Medicine | Business |
| Law | . | 0.15 | 0.35 | 0.21 | 0.60 | 0.04 | 0.20 | -0.12 | -0.03 |
| Science | -0.01 | . | 0.24 | 0.10 | 0.47 | -0.06 | 0.07 | -0.23 | -0.12 |
| Social Science | -0.22 | -0.12 | . | -0.10 | 0.27 | -0.28 | -0.09 | -0.44 | -0.34 |
| Teaching | -0.11 | -0.03 | 0.17 | . | 0.39 | -0.17 | 0.02 | -0.31 | -0.23 |
| Humanities | -0.41 | -0.38 | -0.14 | -0.28 | . | -0.48 | -0.27 | . | -0.53 |
| Engineering | 0.07 | 0.11 | 0.36 | 0.22 | 0.58 | . | 0.20 | -0.16 | -0.03 |
| Health | -0.06 | 0.03 | 0.21 | 0.07 | 0.41 | -0.11 | . | -0.27 | -0.19 |
| Medicine | 0.21 | 0.27 | 0.46 | 0.34 | 0.86 | 0.15 | 0.32 | . | 0.09 |
| Business | 0.14 | 0.21 | 0.42 | 0.28 | 0.64 | 0.09 | 0.27 | -0.03 | . |

*Notes:* In the spirit of Kirkeboen et al. (2016), this table presents the matrix of the payoffs to field $j$ as compared to $k$ (for those who prefer $j$ and have $k$ as next-preferred field) implied by our model. The rows represent completed fields and the columns represent next-ranked fields.

Table B.2: Gender Differences in Returns and Match Effects: Total Earnings

| | Law (1) | Science (2) | Social Science (3) | Teaching (4) | Humanities (5) | Engineering (6) | Health (7) | Medicine (8) | Business (9) |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | Panel A: Female | | | | |
| Returns | 7,079 | 4,261 | 3,212 | 7,245 | -2,402 | 10,040 | 7,442 | 17,444 | 12,056 |
| | (1,185) | (961) | (336) | (148) | (558) | (660) | (286) | (956) | (483) |
| Selection on Gains | 1,418 | 197 | 539 | -196 | 1,245 | 486 | 1,008 | 40 | 1,002 |
| | (417) | (480) | (188) | (115) | (235) | (362) | (172) | (415) | (234) |
| | | | | | Panel B: Male | | | | |
| Returns | 6,042 | 9,170 | 2,507 | 6,451 | -2,739 | 14,226 | 7,013 | 21,592 | 14,093 |
| | (1,368) | (698) | (538) | (258) | (671) | (374) | (604) | (1,200) | (542) |
| Selection on Gains | 2,450 | 1,128 | 1,289 | 625 | 1,548 | 744 | 1,221 | 38 | 1,396 |
| | (482) | (413) | (253) | (155) | (253) | (325) | (264) | (478) | (284) |
| Est. Females = Est. Males | | | | | | | | | |
| $\Delta$ Returns (p-val) | 0.566 | 0.000 | 0.262 | 0.005 | 0.696 | 0.000 | 0.511 | 0.007 | 0.005 |
| $\Delta$ Match Effects (p-val) | 0.105 | 0.141 | 0.017 | 0.000 | 0.379 | 0.596 | 0.499 | 0.997 | 0.285 |

*Notes:* This table presents the estimates obtained from our main regression model, presented in Equation (9). We consider the sum of earnings in 2019 (in USD) instead of the log of earnings to account for the extensive margin. We restrict the sample to students who applied and were accepted through the centralized admission system between 2004 and 2005 and were employed in 2019. The sample includes 137,339 observations. The final two rows of the table report p-values from two additional statistical tests. The $\Delta$ Returns p-values correspond to the null hypothesis that the Female and Male returns are equivalent for a given column. The $\Delta$ Match Effects p-values correspond to the null hypothesis that the Female and Male match effects are equivalent for a given column. All specifications include quadratic polynomials of the college admission scores in mathematics and language, and control for level-effects as defined in the main text, cohort fixed effects and cell fixed effects, where a cell is defined by school type, macro-region, financial-aid relevant score ranges, and gender. For ease of interpretation, $\hat{\lambda}_{ij}$ is standardized within each cell. The $R^2$ of this regression is 0.18.

Table B.3: Gender Differences in Returns and Match Effects: Private Sector Data

| | Law (1) | Science (2) | Social Science (3) | Teaching (4) | Humanities (5) | Engineering (6) | Health (7) | Medicine (8) | Business (9) |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | Panel A: Female | | | | |
| Returns | 0.391 | 0.376 | 0.222 | 0.284 | -0.023 | 0.517 | 0.246 | 0.429 | 0.525 |
| | (0.071) | (0.045) | (0.020) | (0.011) | (0.047) | (0.022) | (0.023) | (0.054) | (0.018) |
| Selection on Gains | 0.058 | 0.009 | 0.039 | 0.021 | 0.069 | 0.016 | 0.065 | -0.013 | 0.019 |
| | (0.023) | (0.022) | (0.011) | (0.008) | (0.019) | (0.013) | (0.013) | (0.023) | (0.009) |
| | | | | | Panel B: Male | | | | |
| Returns | 0.434 | 0.531 | 0.192 | 0.193 | -0.124 | 0.614 | 0.278 | 0.428 | 0.580 |
| | (0.092) | (0.023) | (0.036) | (0.021) | (0.065) | (0.013) | (0.049) | (0.069) | (0.019) |
| Selection on Gains | 0.105 | 0.036 | 0.060 | 0.066 | 0.087 | 0.004 | 0.066 | 0.032 | 0.052 |
| | (0.030) | (0.014) | (0.016) | (0.011) | (0.023) | (0.011) | (0.019) | (0.027) | (0.010) |
| Est. Females = Est. Males | | | | | | | | | |
| $\Delta$ Returns (p-val) | 0.710 | 0.002 | 0.459 | 0.000 | 0.203 | 0.000 | 0.551 | 0.983 | 0.025 |
| $\Delta$ Match Effects (p-val) | 0.224 | 0.307 | 0.289 | 0.001 | 0.532 | 0.489 | 0.942 | 0.203 | 0.014 |

*Notes:* This table presents the estimates obtained from our main regression model, presented in Equation (9). We consider the earnings of workers in the private sector. The sample includes 78,336 observations of students who applied and were accepted through the centralized admission system between 2004 and 2007 and were employed in the private sector in 2019. The final two rows of the table report p-values from two additional statistical tests. The $\Delta$ Returns p-values correspond to the null hypothesis that the Female and Male returns are equivalent for a given column. The $\Delta$ Match Effects p-values correspond to the null hypothesis that the Female and Male match effects are equivalent for a given column. All specifications include quadratic polynomials of the college admission scores in mathematics and language, and control for level-effects as defined in the main text, cohort fixed effects and cell fixed effects, where a cell is defined by school type, macro-region, financial-aid relevant score ranges, and gender. For ease of interpretation, $\hat{\lambda}_{ij}$ is standardized within each cell. The $R^2$ of this regression is 0.25.

Table B.4: Fertility: Number of children 13 years after college application

| | Law (1) | Science (2) | Social Science (3) | Teaching (4) | Humanities (5) | Engineering (6) | Health (7) | Medicine (8) | Business (9) |
|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Female** | | | | | | | | | |
| Returns | -0.184 | -0.239 | -0.072 | 0.119 | -0.151 | -0.063 | 0.087 | -0.006 | -0.005 |
| | (0.050) | (0.040) | (0.022) | (0.015) | (0.040) | (0.028) | (0.019) | (0.033) | (0.023) |
| Selection on Gains | 0.060 | 0.001 | -0.006 | -0.020 | 0.022 | -0.016 | -0.010 | 0.018 | 0.012 |
| | (0.018) | (0.020) | (0.012) | (0.011) | (0.016) | (0.016) | (0.011) | (0.015) | (0.011) |
| **Panel B: Male** | | | | | | | | | |
| Returns | -0.241 | -0.345 | -0.277 | -0.136 | -0.436 | -0.126 | -0.142 | -0.144 | -0.122 |
| | (0.049) | (0.023) | (0.030) | (0.022) | (0.036) | (0.015) | (0.031) | (0.037) | (0.021) |
| Selection on Gains | 0.058 | 0.043 | 0.012 | -0.003 | 0.047 | -0.008 | 0.020 | 0.046 | -0.018 |
| | (0.018) | (0.014) | (0.014) | (0.012) | (0.014) | (0.013) | (0.013) | (0.015) | (0.011) |
| Est. Females = Est. Males | | | | | | | | | |
| $\Delta$ Returns (p-val) | 0.415 | 0.018 | 0.000 | 0.000 | 0.000 | 0.040 | 0.000 | 0.004 | 0.000 |
| $\Delta$ Match Effects (p-val) | 0.929 | 0.075 | 0.338 | 0.294 | 0.239 | 0.687 | 0.091 | 0.177 | 0.059 |

*Notes:* This table presents the estimates obtained from our main regression model, presented in Equation (9). The sample includes 137,339 observations of students who applied and were accepted through the centralized admission system between 2004 and 2007. The final two rows of the table report p-values from two additional statistical tests. The $\Delta$ Returns p-values correspond to the null hypothesis that the Female and Male returns are equivalent for a given column. The $\Delta$ Match Effects p-values correspond to the null hypothesis that the Female and Male match effects are equivalent for a given column. All specifications include quadratic polynomials of the college admission scores in mathematics and language, and control for level-effects as defined in the main text, cohort fixed effects and cell fixed effects, where a cell is defined by school type, macro-region, financial-aid relevant score ranges, and gender. For ease of interpretation, $\hat{\lambda}_{ij}$ is standardized within each cell. The $R^2$ of this regression is 0.05.

# C Child Penalties and Gender Norms

This section details how we leverage the administrative data to estimate the child penalties and gender norms measures discussed in Section 4 of the main body of the paper.

## C.1 Child Penalties

Following Kleven et al. (2019b), we estimate child penalties with the model:

$$\tilde{Y}_{it} = \sum_{k \neq -2} \beta_j D_{it}^k + \mu_a + \gamma_t + \nu_{it}, \qquad (16)$$

where $D_{it}^k \equiv \mathbb{1}[t = c + k]$ is a binary variable that indicates the time relative to the period in which the first child was born $c$. $\mu_a$ are age-fixed effects that account for the life cycle effects on the outcome variable, and $\gamma_t$ are time-fixed effects that control for temporal trends at the 6-month frequency. We omit the time binary variable corresponding to $t = -2$ since, in our case, it represents the period of child conception. Our primary outcome variable is labor market earnings in period $t$ relative to the period of child conception $t^*$, i.e., $\tilde{Y}_{it} = Y_{it}/Y_{it^*}$.

We estimate the impacts of children on women and men separately and define the child penalty at event time $t$ as $\hat{\beta}_t^m - \hat{\beta}_t^w$, which measures the percentage by which women fall behind men due to children. Figure C.1 shows the effects of parenthood on earnings across fields of study. To use a symmetric window, and since we have earnings starting only in 2015, we focus on college graduates whose first child was born in 2016 or 2017. This figure also reports the estimated child penalty at time $t = 4$. We have a more limited window of coverage compared to existing studies (Kleven et al., 2019a) and can estimate child penalties only up to 4 years after the birth of a child, so our estimates are relatively short-run. Nonetheless, most evidence shows a somewhat immediate drop in mothers' earnings, which changes minimally over time.

Table C.1 complements previous evidence and reports the estimated child penalty before child conception, at time $t = -4$, and after it, at time $t = 4$; and Appendix Figure C.2 reports child penalty estimates for each field of study. There is a vast amount of heterogeneity, with Science and Social Science exhibiting the largest penalties (36% and 32% percent, respectively) and Business and Medicine exhibiting the lowest child penalties. The average penalty across majors is a 16% reduction in earnings for women relative to men after the birth of their first child, with a noise-adjusted standard deviation of 10%. Although the heterogeneity we document alludes to an empirical interaction between major choice, gender, earnings, and fertility, the evidence reported in Figure C.2 is not causal.[27]

[27] An econometric concern is that we observe child penalties for a selected sample of parents who choose to have children earlier. Melentyeva and Riedel (2023) finds that age heterogeneity matters but

Another explanation is that some majors lead to careers in industries or occupations with more flexible work arrangements, which could help mitigate or amplify the child penalty. Additionally, as suggested by the evidence in Table 5, individuals who prioritize work-life balance and anticipate having children may choose majors perceived as more family-friendly. However, certain industries—often aligned with specific majors—may enforce stronger gender norms or biases. In traditionally male-dominated fields like Engineering or Science, the child penalty might be more or less pronounced depending on implicit or explicit biases against women taking maternity leave or reducing work hours.

## C.2 Gender Norms

We follow the pioneering work by Bertrand et al. (2015) and construct a measure of major-specific gender norms associated with the distribution of relative labor earnings within households. We focus on graduates who had their first child after they obtained their college degree and on their partners (i.e., a couple). For each couple of parents, we use their labor market earnings from the third and fourth quarter before childbirth and focus on couples where both members earn positive income and are between 20 and 40 years old. We define $Relative\ Earnings_i$ as $\frac{Woman\ Earnings_i}{Woman\ Earnings_i + Man\ Earnings_i}$, where $i$ indexes the couple, and $Woman\ Earnings_i$ and $Male\ Earnings_i$ are the total labor income of the will-be mothers and fathers, respectively.

Our proxy for the progressivity of gender norms is measured by the size of the cliff of $Relative\ Earnings_i$ at 0.5. To gauge the magnitude of the drop at the point where the female starts to earn more than the male, we calculate the fraction of couples in each of twenty 0.05 relative income bins and project it on a discontinuity indicator while controlling for quadratic polynomials at each side of the 0.5 cutoff. Table C.2 presents the OLS estimates associated with the discontinuity indicators obtained from separate regressions for each of our nine fields of study. Panel (a) presents the results when we focus on female graduates (and their partners), and Panel (b) repeats the exercise but focuses on male graduates (and their partners).[28]

Figure C.3 depicts, for each of the nine fields of study, the frequency distribution of relative earnings grouped in 20 bins, along with a lowess (locally weighted scatterplot smoothing) estimate of the distribution on each side of 0.5, the point where the woman starts to earn more than the man. In most fields of study, the distribution of relative earnings exhibits a sharp drop at 0.5, with the largest drops in Law, Science, Engineering,

that child penalties are largest for younger mothers as they are more likely to disconnect from the labor market in years with steep career growth.

[28]Overall, we find similar variation in gender norms across fields of study, independently of whether we focus on male or female graduates (and their partners). Two exceptions are Humanities and Medicine, which show smaller and larger drops (at the point where the female starts to earn more than the male), respectively, when the graduate is male.

Medicine, and Business and the smallest in Social Science, Teaching, Humanities, and Health.

What drives the variation in the estimated cliffs at 0.5? Besides gender norms, a few other features could contribute to the variation in the estimated cliffs. First, majors offering students a menu of jobs with more flexible and less non-linear pay schedules allow for choices that generate a smoother within-household earnings distribution (Goldin, 2024). From that perspective, the estimated cliffs are not a product of norms but a consequence of differences in major-specific access to jobs. To partly gauge the extent of that, we corroborate our norm estimates in publicly available survey data, where we can further probe the sensitivity of the estimates to differences in labor hours. As shown by Figure C.4, we find broadly similar norm estimates among the subset of couples with full-time jobs whose hours worked per week are 40 or more.[29] Second, some majors have closer ties to the public sector, and variation in public sector access could contribute to variation in the cliffs. We do not find evidence of this as Health, Medicine, and Teaching all provide strong access to the public sector in Chile. Third, some scholars have noted that cliff estimates may be sensitive to bunching at 0.5, casting doubt on its interpretation as variation in gender norms, especially when using survey data (Binder and Lam, 2022; Hederos and Stenberg, 2022; Zinovyeva and Tverdostup, 2021). In our *administrative* records, however, few couples (7%) have equal earnings. Figure C.5 further investigates the potential impact of bunching on interpreting differences in cliffs as variations in gender norms. Panel (a) presents the cliffs when pooling data across fields of study, while Panel (b) shows the cliffs after removing cases where parents have equal earnings. Reassuringly, the cliffs are similar across panels.

We, therefore, argue that the variation in the estimated cliffs can be interpreted as variation in breadwinner norms across fields of study.

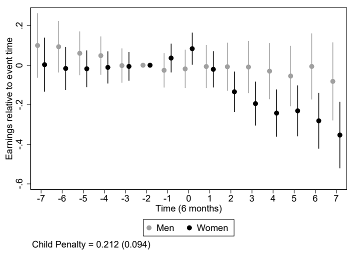
[29]The patterns in the estimated cliffs using survey data remain broadly the same. The CASEN survey groups Health and Medicine into a single field of study, so we cannot estimate the cliffs separately for Health and Medicine.

Table C.1: Child Penalties

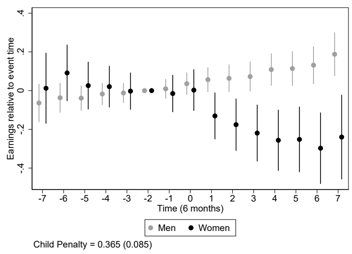
| | Law (1) | Science (2) | Social Science (3) | Teaching (4) | Humanities (5) | Engineering (6) | Health (7) | Medicine (8) | Business (9) |
|---|---|---|---|---|---|---|---|---|---|
| Female - Male Gap Before ($t = -4$) | -0.060 | 0.038 | 0.020 | 0.008 | -0.099 | -0.046 | 0.021 | -0.093 | -0.032 |
| | (0.064) | (0.058) | (0.049) | (0.023) | (0.098) | (0.028) | (0.038) | (0.042) | (0.027) |
| Female - Male Gap After ($t = 4$) | -0.212 | -0.365 | -0.321 | -0.163 | -0.271 | -0.085 | -0.197 | 0.077 | -0.076 |
| | (0.094) | (0.085) | (0.072) | (0.034) | (0.144) | (0.041) | (0.055) | (0.061) | (0.040) |
| Number of observations | 24,155 | 24,436 | 60,385 | 131,242 | 19,859 | 95,012 | 71,754 | 27,935 | 80,003 |

*Notes:* This table presents estimates obtained from estimating equation 16. Specifically, it shows the estimated child penalty (and its standard error) before child conception, at time $t = -4$, and after it, at time $t = 4$.

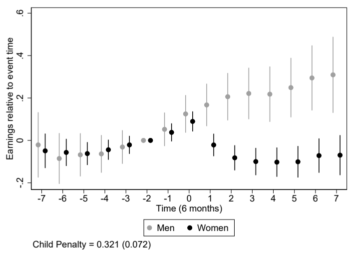
Figure C.1: Child Penalty by Field of Study



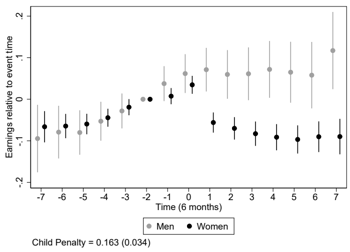

(a) Law



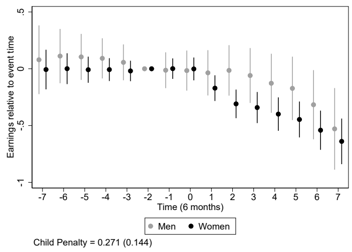

(b) Science



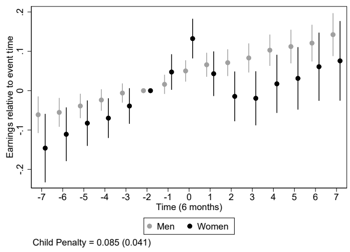

(c) Social Science



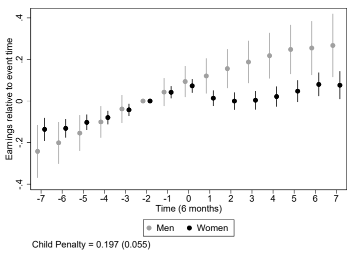

(d) Teaching



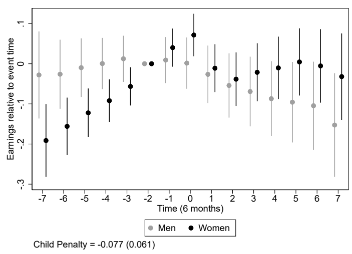

(e) Humanities



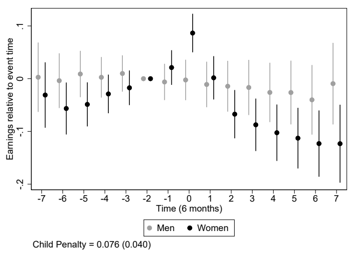

(f) Engineering




(g) Health



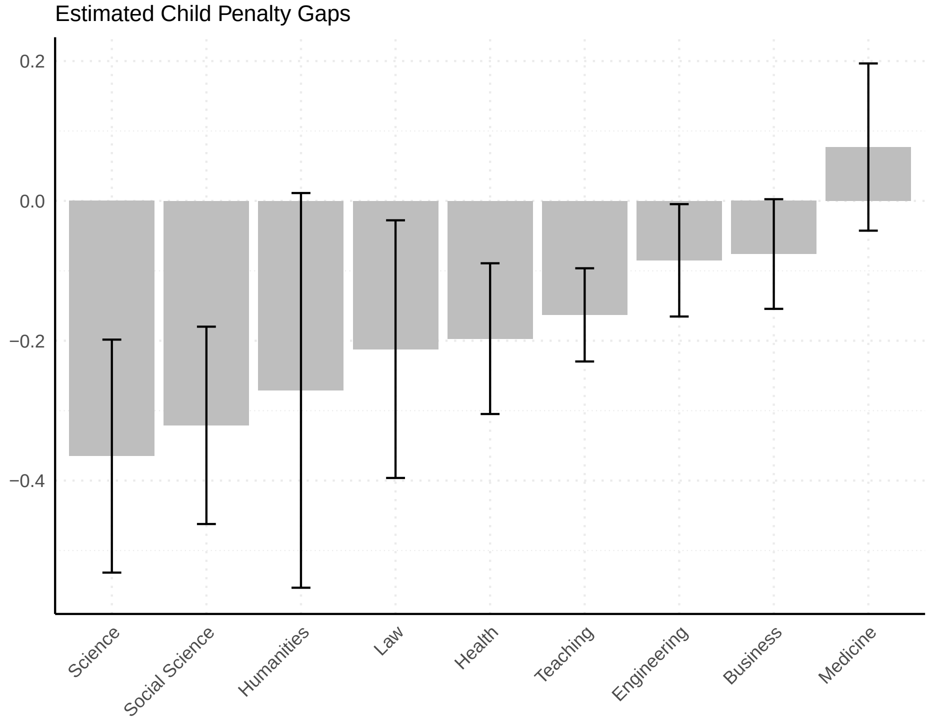

(h) Medicine




(i) Business

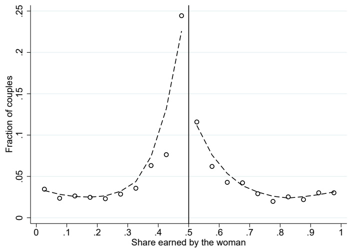
Notes: These figures show the percentage effects of parenthood on earnings across event time for men and women. Each panel corresponds to one of the nine fields of study considered in our analysis. We consider college graduates who had their first child between 2016 and 2017 and after their graduation. The figure also displays the average child penalty at the end of our time window (4 years after childbirth). Earnings are not conditional on employment status, and the effects include extensive and intensive margins.

Figure C.2: Child Penalty Gaps Across Fields of Study

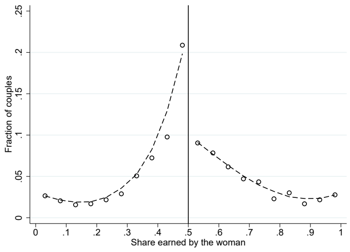



Notes: This figure shows the estimated child penalty gap four years after birth (and the corresponding confidence interval). We consider college graduates who had their first child between 2016 and 2017 and after graduation. Earnings are not conditional on employment status, and the effects include extensive and intensive margins. Estimation follows Kleven et al. (2019b) and for additional details, see Appendix C.

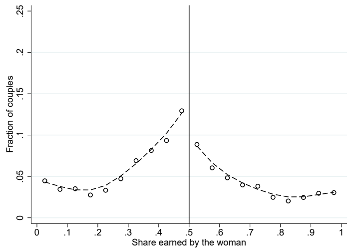
Figure C.3: Gender Norms by Field of Study



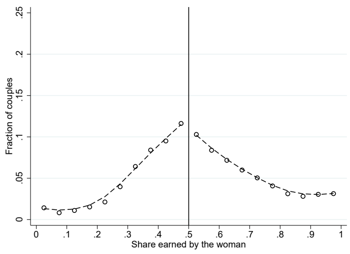

(a) Law



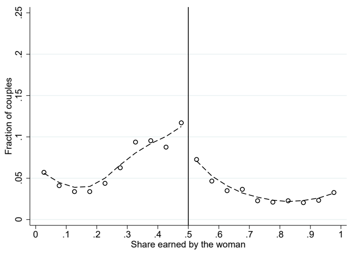

(b) Science



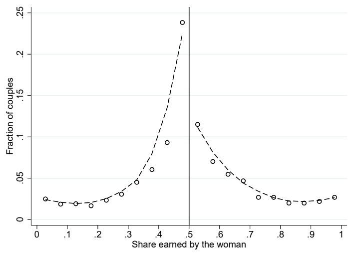

(c) Social Science



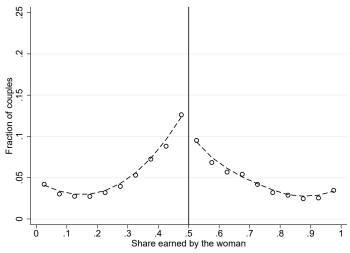

(d) Teaching



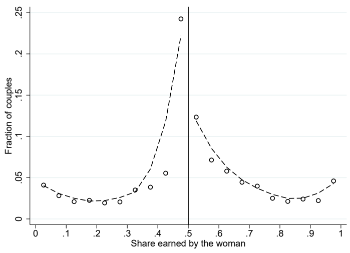

(e) Humanities



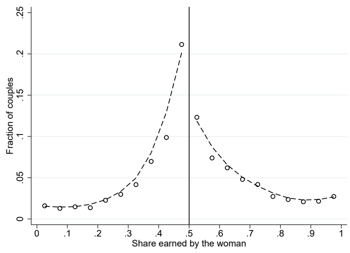

(f) Engineering




(g) Health



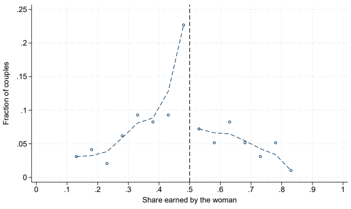

(h) Medicine



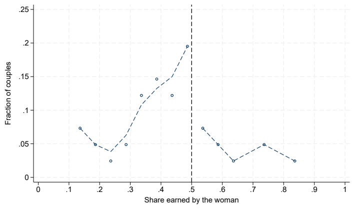

(i) Business

Notes: These figures report the relative income distribution for females who graduated from different fields of study. The sample includes couples of parents who both earn positive income. We use the observation from the third and fourth quarters before childbirth. Each dot is the fraction of couples in a 0.05 relative income bin. The vertical line indicates the relative income share=0.5. The dashed line is the lowess smoother applied to the distribution, allowing for a break at 0.5.

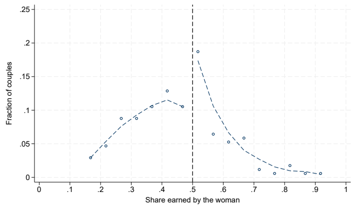
Figure C.4: Gender Norms by Field of Study: Full-time workers (CASEN survey)



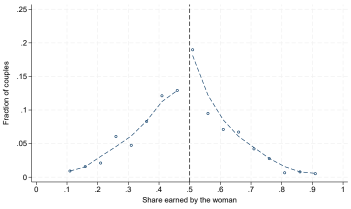

(a) Law



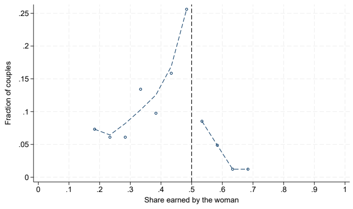

(b) Science



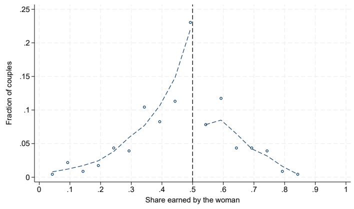

(c) Social Science



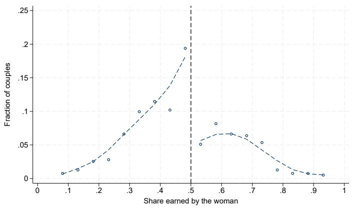

(d) Teaching



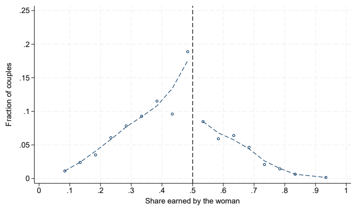

(e) Humanities




(f) Engineering



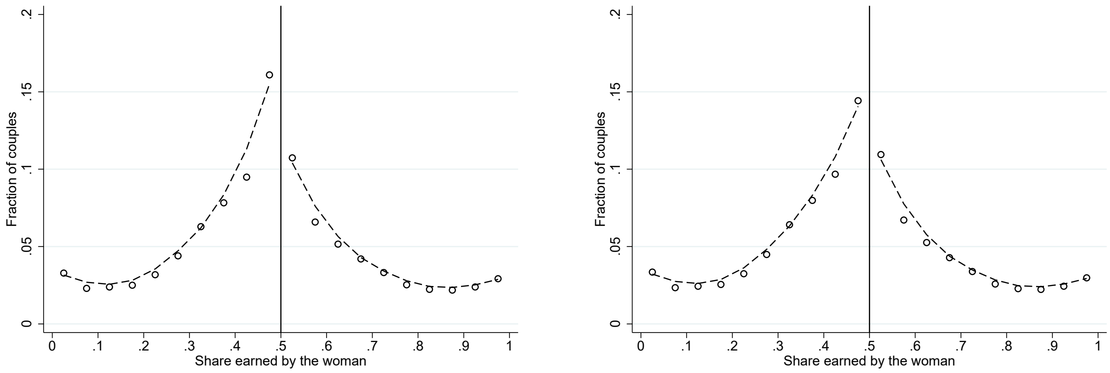

(g) Health and Medicine




(h) Business

Notes: These figures report the distribution of relative income separately for females who graduated from different fields of study. The sample includes couples in the household survey CASEN, where both earn positive income and have full-time jobs (work more than 40 hours a week). Each dot is the fraction of couples in a 0.05 relative income bin. The vertical line indicates the relative income share=0.5. The dashed line is the lowess smoother applied to the distribution, allowing for a break at 0.5. Since the survey records do not separate Medicine from Health, both fields are embedded into the Health figure.

Figure C.5: Gender Norms: Removing bunching at 0.5 (pooled)




(a) All

(b) No Bunching

Notes: These figures report the distribution of relative income. The sample includes couples of parents who both earn positive income. Panels (a) consider all parents, while Panel (b) removes cases in which parents report the same income. We use the observation from the third and fourth quarters before childbirth. Each dot is the fraction of couples in a 0.05 relative income bin. The vertical line indicates the relative income share=0.5. The dashed line is the lowess smoother applied to the distribution, allowing for a break at 0.5.

Table C.2: Gender Norms

| | Law | Science | Social Science | Teaching | Humanities | Engineering | Health | Medicine | Business |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Panel (a): Female graduates (and their partners) | | | | | | | | | |
| Break | -0.104 | -0.095 | -0.048 | -0.023 | -0.054 | -0.099 | -0.036 | -0.080 | -0.080 |
| | (0.034) | (0.019) | (0.007) | (0.006) | (0.014) | (0.028) | (0.005) | (0.039) | (0.021) |
| Panel (b): Male graduates (and their partners) | | | | | | | | | |
| Break | -0.109 | -0.046 | -0.033 | -0.019 | -0.012 | -0.078 | -0.008 | -0.143 | -0.111 |
| | (0.019) | (0.013) | (0.011) | (0.011) | (0.012) | (0.011) | (0.010) | (0.026) | (0.019) |

*Notes:* This table reports the estimated discontinuity in the distribution of relative earnings of individuals from different fields of study. The dependent variable is the fraction of couples. We calculate the fraction of couples in each of the twenty 0.05 relative income bins and project it on a discontinuity indicator while controlling for a quadratic polynomial at each side of the 0.5 cutoff. This table presents the OLS estimates of the discontinuity indicators obtained from separate regressions for each field of study. Panel (a) considers mothers who graduated from a field of study and their couples, and Panel (b) considers fathers who graduated from a field of study and their couples. We use the observations from the third and fourth quarters before childbirth and focus on couples where both members earn positive income.

# D Counterfactual Details

This section reports additional details related to the counterfactual policies we analyze in Section 5. We discuss our implementation of the deferred acceptance algorithm, offer details on the machine learning model used to predict graduation probabilities, describe the bootstrap procedure used in our counterfactual analysis, and the conclusion provides additional details underpinning the main counterfactual results in the main paper.

## D.1 Deferred Acceptance Algorithm

We use the following algorithm to produce an outcome of the student-proposing Deferred Acceptance algorithm.

**Step 1)** Each student proposes to her first choice. Each program tentatively assigns seats to its proposers one at a time, following their priority order based on the weighted score. Students are rejected if no seats are available at the time of consideration.

In general, in

**Step k)** Each student who was rejected in the previous step proposes to her next best choice. Each program considers the students it has tentatively assigned together with its new proposers and tentatively assigns its seats to these students one at a time following the program's priority order based on the weighted score. The student is rejected if no seats are available when she is considered.

The algorithm terminates either when there are no new proposals or when all rejected students have exhausted their rank order list of preferences. When introducing quotas, we apply a precedence order by first processing the open seats and then the gender-specific seats. Following Dur et al. (2018), this order of precedence maximizes the impact of quotas.

## D.2 Prediction Accuracy and Summary Statistics

We use statistical learning methods to predict graduation between the time of being accepted and up to thirteen years after application. In particular, we train a Gradient Boosting Model (GBM) to generate predictions. Predictors include the income quintile of the student at the time when they applied to college, type of high school and health insurance, PSU scores (Math, Language, History, and Science), parent's educational attainment, indicators for applying to different universities and majors, indicators for acceptance at different universities, preferences, and the control functions from the choice model.

We train a separate GBM for each field to generate an out-of-sample predicted graduation probability for each field for each student. We make out-of-sample predictions for all students in the admissions process in 2007. We use applicants from the years 2008 and 2010 for fitting and out-of-sample tuning. Chilean students can apply to college for multiple years, and as a consequence, applicants in the year 2007 (our validation year) might appear in our training sample for the years 2008-2010. To avoid this, we restrict our sample so that students appear only in the last year they applied to college. To improve model performance, we fine-tune the parameters of each GBM (i.e., number of boosting rounds, maximum tree depth, and learning rate) for each field separately using 5-fold cross-validation and a grid search on the training sample. Specifically, we identify the combination of parameters that minimizes the Brier score averaged across the 5 cross-validation iterations.

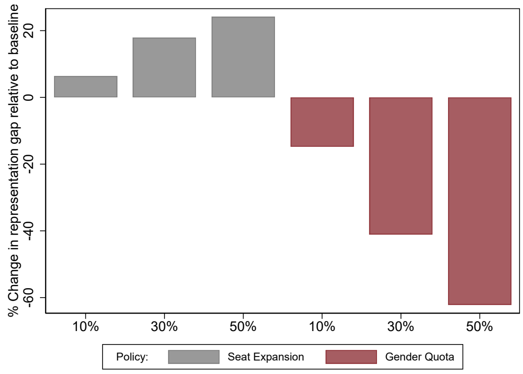
Appendix Figure D.2 reports forecast bias assessments. The forecast coefficients are statistically equal to one for fields of study that are heavily impacted in the counterfactual analysis. The model tends to underpredict graduation probabilities in Teaching, Humanities, and Health. These three fields account for less than seven percent of the roughly four percent of women affected in the counterfactuals and around eight percent of the five percent of affected men. Importantly, the graduation probabilities are forecast unbiased for Engineering, Business and Science, the three most important fields for comparison across counterfactual scenarios.

## D.3 Causal Graduation Probabilities

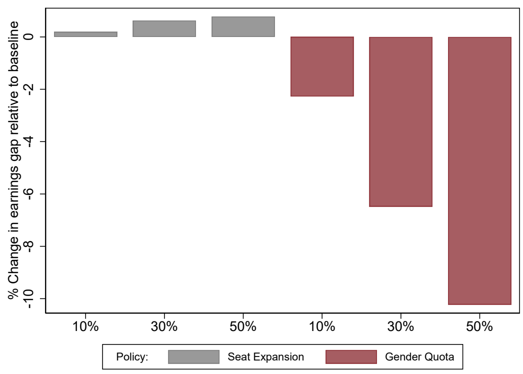
We use machine learning methods to predict graduation probabilities in the main body of the paper, but an alternative approach is to estimate a causal model of graduation. In this section, we assess the sensitivity of our main counterfactual results to the use of graduation probabilities estimated from a causal model. Specifically, we estimate graduation probabilities using Equation (9) in the main body of the paper (i.e., using graduation as an outcome and assignment as the treatment).

Appendix Figure D.1 reports estimates analogous to Figure 5. Reassuringly, the results are qualitatively and quantitatively similar when using graduation probabilities estimated in the causal model.

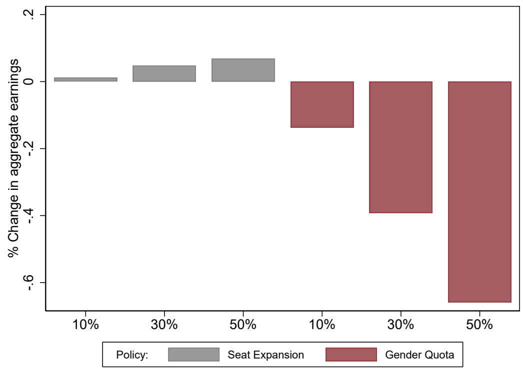
Figure D.1: Counterfactual Policies



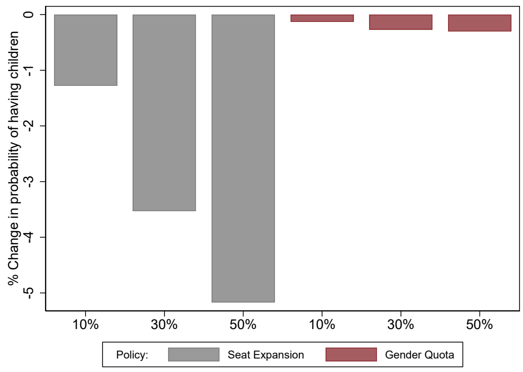

(a) Representation Gap in Engineering




(b) Total Earnings Gap



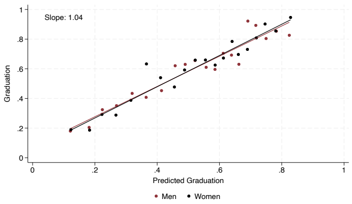

(c) Total Earnings



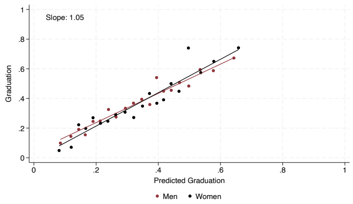

(d) Total Fertility

Notes: These figures report the changes (relative to baseline) implied by different counterfactual scenarios using the predicted graduation obtained from our causal model. We consider 10, 30, and 50% seat expansions in Engineering programs (gray bars) and a 10, 30, and 50% quota for women in Engineering (red bars). Panel (a) shows the impacts on the Engineering representation gap. Panel (b) reports the impacts on the total gender earnings gap. Panels (c) and (d) show the total impacts on earnings and fertility. The sample includes the 87,599 students who applied through the centralized admission system in 2007.

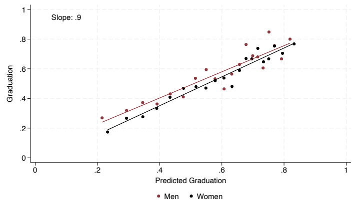
Figure D.2: Predictive Accuracy



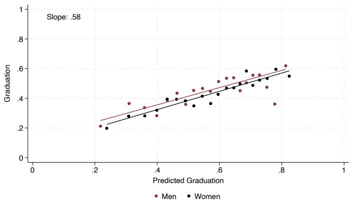

(a) Law



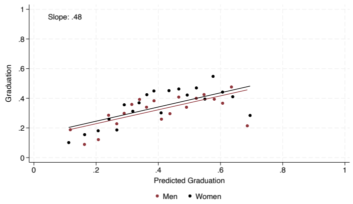

(b) Science



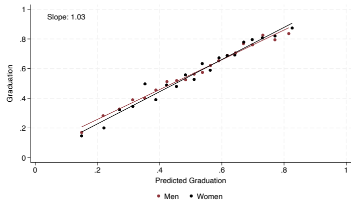

(c) Social Science



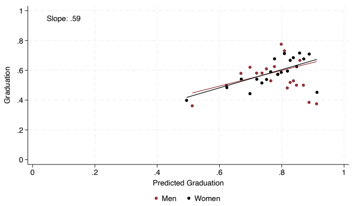

(d) Teaching



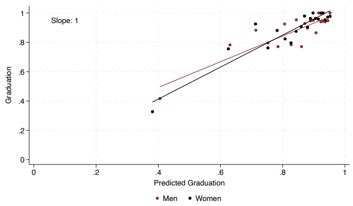

(e) Humanities



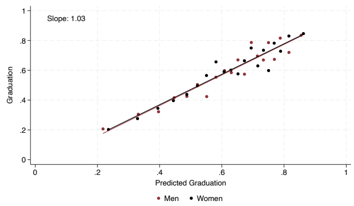

(f) Engineering




(g) Health



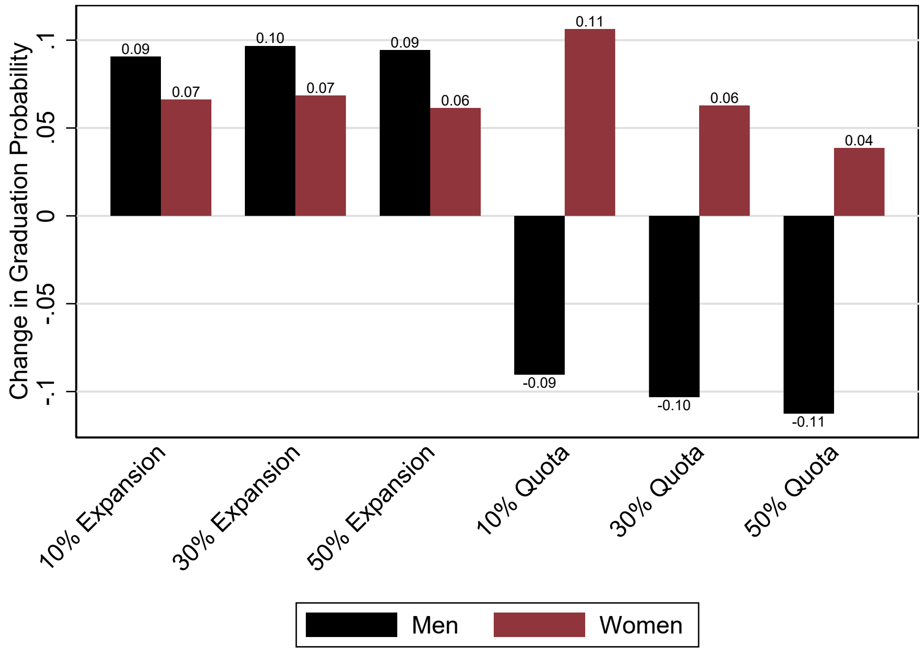

(h) Medicine




(i) Business

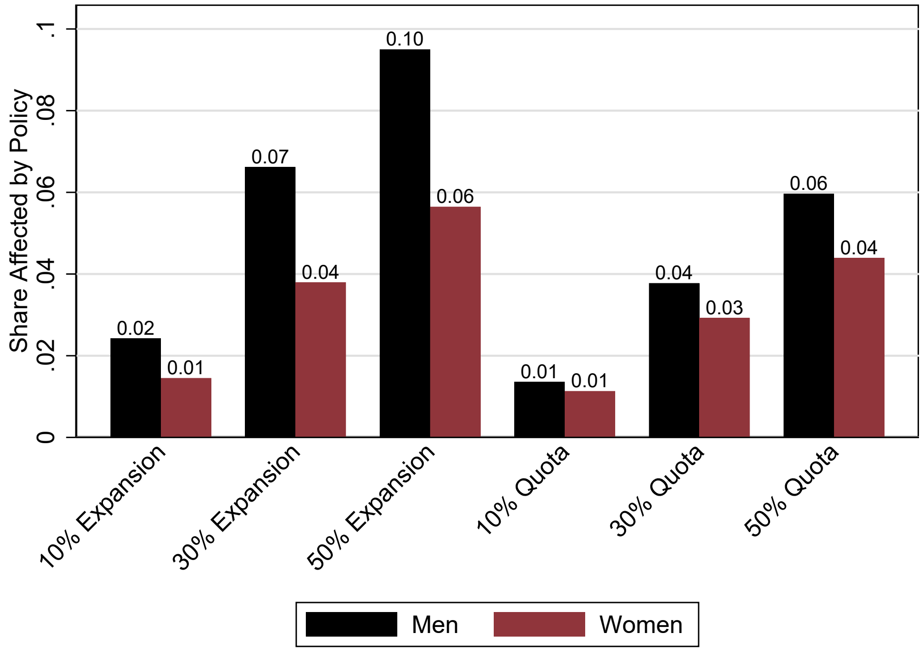
Notes: These figures report binscatter plots of graduation on out-of-sample predicted graduation rates separately for each field of study among accepted applicants in 2007.

Figure D.3: Change in Graduation Probabilities



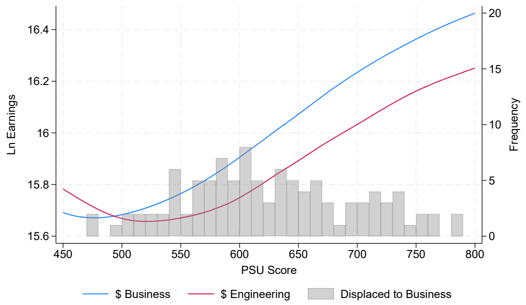

Notes: This figure shows the change in graduation probabilities—as predicted by our Gradient Boosting Model—for all male and female applicants who are assigned in each counterfactual scenario.

Figure D.4: Share Affected by Each Policy

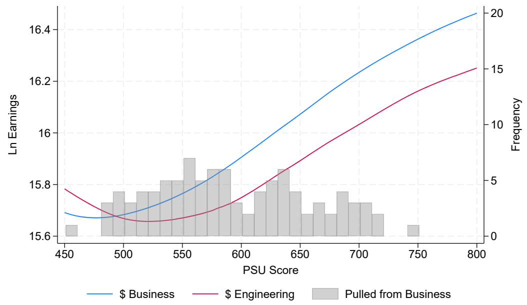



Notes: This figure shows the percentage of male and female applicants directly or indirectly affected in each counterfactual scenario.

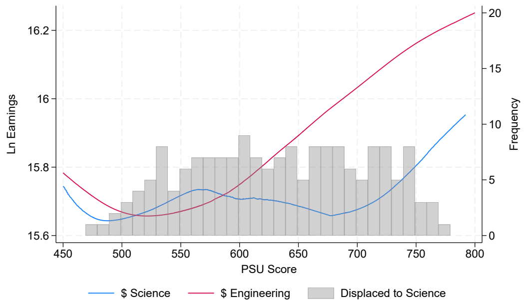
Figure D.5: Displaced Students



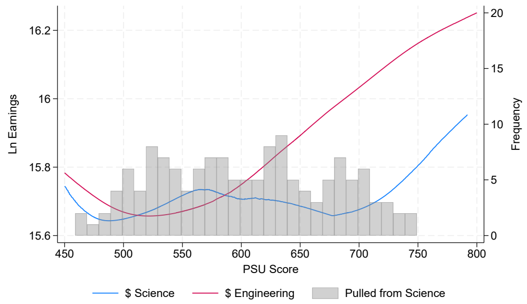

(a) Pushed to Business from Engineering



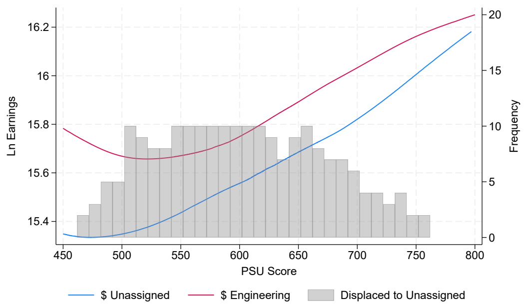

(b) Pulled from Business into Engineering



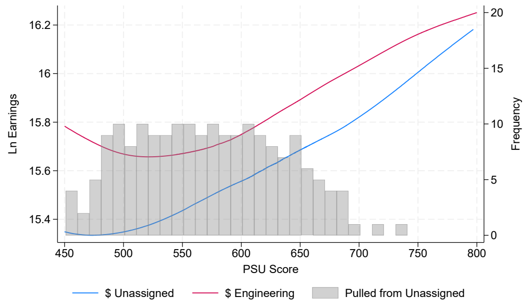

(c) Pushed to Science from Engineering




(d) Pulled from Science into Engineering




(e) Pushed to Unassigned from Engineering




(f) Pulled from Unassigned into Engineering

Notes: These figures present log earnings as a function of test scores for graduates from different fields of study. Gray bars show the test score distribution of students reshuffled across fields under the counterfactual quota policy of 50% in Engineering. We focus on students who were either “displaced to” or “pulled from” the three main fallback options for Engineering: Business, Science, and Unassigned.

Table D.1: Origin of Affected Students: 50% Engineering Seat Expansion

| Fields | Women: Percent among women moved into Engineering | Women: Percent among all women | Men: Percent among men moved into Engineering | Men: Percent among all men |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Panel (a): Effect in Engineering | | | |
| Law | 0.17 | 0.01 | 0.09 | 0.01 |
| Science | 12.16 | 0.45 | 16.24 | 1.24 |
| Social Science | 1.51 | 0.06 | 0.84 | 0.06 |
| Teaching | 5.20 | 0.19 | 2.61 | 0.20 |
| Humanities | 5.54 | 0.21 | 2.84 | 0.22 |
| Health | 1.68 | 0.06 | 0.60 | 0.05 |
| Medicine | 0.00 | 0.00 | 0.00 | 0.00 |
| Business | 12.25 | 0.46 | 6.79 | 0.52 |
| Unassigned | 55.45 | 2.07 | 64.63 | 4.94 |
| All affected Engineering | 100.00 | 3.73 | 100.00 | 7.64 |
| | Panel (b): Effect in Other Fields | | | |
| All affected other fields | - | 1.92 | - | 1.86 |

*Notes:* This table presents a breakdown of changes in assignment and returns for students whose field of study was affected by a 50% seat expansion in Engineering relative to baseline. Panel (a) presents the impact on Engineering. Columns (1) and (2) present the impact for women whose counterfactual assignment is Engineering. Column (1) shows the percentage of those affected (by baseline field of study) out of all women whose counterfactual field is Engineering. Column (2) shows the percentage of all women. Columns (3) and (4) present the analogous figures for men. Panel (b) summarizes the impact on women and men who experienced a reallocation in the counterfactual scenario but were neither pushed into nor displaced from Engineering.

Table D.2: Origin and Destination of Affected Students: 50% Engineering Quota

| Fields | Women | | Men | |
|---|---|---|---|---|
| | Percent among women moved into Engineering | Percent among all women | Percent among men displaced from Engineering | Percent among all men |
| | (1) | (2) | (3) | (4) |
| | Panel (a): Effect in Engineering | | | |
| Law | 0.24 | 0.01 | 0.27 | 0.01 |
| Science | 14.98 | 0.58 | 26.29 | 1.37 |
| Social Science | 1.20 | 0.05 | 1.22 | 0.06 |
| Teaching | 4.78 | 0.19 | 3.33 | 0.17 |
| Humanities | 5.10 | 0.20 | 3.26 | 0.17 |
| Health | 1.75 | 0.07 | 2.72 | 0.14 |
| Medicine | 0.08 | 0.00 | 0.07 | 0.00 |
| Business | 13.78 | 0.54 | 10.94 | 0.57 |
| Unassigned | 57.45 | 2.24 | 49.18 | 2.57 |
| All affected Engineering | 100.00 | 3.90 | 100.00 | 5.23 |
| | Panel (b): Effect in Other Fields | | | |
| All affected other fields | - | 0.49 | - | 0.74 |

*Notes:* This table presents a breakdown of changes in assignment and returns for students whose field of study was affected by a 50% female quota in Engineering relative to baseline. Panel (a) presents the impact on Engineering. Columns (1) and (2) present the impact for women whose counterfactual assignment is Engineering. Column (1) shows the percentage of those affected (by baseline field of study) out of all women whose counterfactual field is Engineering. Column (2) shows the percentage of all women. Columns (3) and (4) present the analogous for men displaced from Engineering into other fields of study (each row). Panel (b) summarizes the impact on women and men who experienced a reallocation in the counterfactual scenario but were neither pushed into nor displaced from Engineering.

# E Appendix References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