Returns to Fields of Study and the Gender Earnings Gap*

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February 2024

Abstract

This paper studies the interplay between major returns, preferences, and market design in explaining the gender earnings gap. Information on preferences allows us to estimate the major impacts while accounting for selection on rich sources of preference heterogeneity. We use this to estimate pecuniary returns to majors and fertility impacts. We find substantial heterogeneity in pecuniary and fertility impacts, with sizable gender differences in each. We find that pecuniary returns are most predictive of male gender choices and the opposite is true for females, providing empirical evidence about an important factor that causes a rift in the educational decisions of men and women. While there are sizable within-major gender differences in returns, we find that most of the college graduate gender gap is explained by differences in representation. Against this backdrop, we take preferences as given and consider policy-relevant counterfactuals leveraging the algorithmic rules embedded in a centralized assignment system. Our results suggest that slight gender-specific quotas can substantially reduce the gender earning gap among college graduates with minimal impact on efficiency.

Keywords: returns to majors, gender gaps, centralized assignment
JEL Classification: I24, I26, J01, J16

*We thank the Ministerio de Desarrollo Social of Chile for their help in accessing the data. The views expressed here are those of the authors and do not reflect the views of the Ministerio de Desarrollo Social. Camila Brown provided outstanding research assistance.
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1 Introduction

Despite considerable gender convergence in earnings over time, a sizeable gap remains around the world (Goldin, 2014a, Kleven et al., 2019). Through recent decades, there has also been an increase in within-group inequality at the top of the earnings distribution (Autor et al., 2005, Lemieux, 2006). In this regard, many observers have pointed to the potential role that major choice plays in explaining earnings inequality among college graduates, with Altonji et al. (2012) finding that the dispersion in returns to majors is as large as the dispersion in the returns to college. These trends underscore the potential importance of major choice on the persistence of gender inequality in labor market outcomes (Goldin et al., 2017, Sloane et al., 2021). Nonetheless, a systematic study of gender differences in preferences and labor market returns has been lacking.

Previous work has struggled empirically in linking preferences, graduation, earnings, and fertility while methodologically accounting for the self-selection of individuals to majors. Existing literature either documents gender differences in major choice (Bordon et al., 2020, Brenoe and Zolitz, 2020, Zafar, 2009), but does not assess its impact on the gender earnings gap, or study the role of field of study on earnings (Dahl et al., 2020, Hastings et al., 2013, Kirkeboen et al., 2016) but omits the role of gender differences in preferences. A separate literature documents evidence about the so-called child penalty gap around the world and its implications for gender gaps (Angelov et al., 2016, Gallen, 2023, Kleven et al., 2019), but is silent about the potential influence that has on the major choice of females. A growing literature emphasizes the importance of identity for decion-makers (Akerlof and Kranton, 2000) and the importance that has for observed gender differences (Bertrand, 2011, 2020, Bursztyn et al., 2017, Del Carpio and Guadalupe, 2022). In this paper, we overcome previous limitations by focusing on a setting, the Chilean higher education system, that allows the linkage of students' preferences for majors to their educational attainment, labor market earnings, and fertility outcomes while allowing us to shed light on the various factors that generate rifts in the educational trajectories of men and women.

We build into our empirical framework with descriptive evidence. Similar to findings in Sloane et al. (2021) for the United States, we find slow convergence in gender representation across majors, which are important sources of the gap.[1] A systematic decomposition shows that 82 percent of the raw 19.2% gender earnings gap among college graduates is due to representation. These descriptive findings might motivate policies that reallocate women from lower-earning to higher-earning fields of study, especially Science and Engineering. However, for a formal assessment of such policies, one needs gender-specific causal estimates of returns to majors and, importantly, estimates of match effects to account for the potential mismatch hypothesis (Arcidiacono and Lovenheim, 2016). Our conceptual framework models these various important contributors to the gender earning gap.

We adopt a conceptual framework that disciplines how we think about major choices and

[1]For example, thirty percent of Chilean male graduates earn an Engineering degree, while less than ten percent of female graduates do the same. In contrast, nearly thirty percent of female graduates earn a Teaching degree, with slightly over ten percent of male graduates doing the same. The sizable earnings differences between Teaching and Engineering graduates is a useful case study emphasizing differences in representation.

how those choices are intrinsically linked to the potential outcomes that students weigh when making decisions. This framework—that borrows from the school choice literature (Abdulkadiroglu et al., 2020)—also leads to an estimation strategy that allows us to decompose the gender earnings gap in new ways. Our approach assumes that the only source of bias in returns to the field of study is due to the correlation between unobserved preference heterogeneity, major choice, and earnings, and it allows us to construct control functions to flexibly account for self-selection. This framework captures both average returns separately for men and women and empirically assesses the importance of match effects. The latter is important when considering reallocation policies, which are our focus in the final part of the paper. Although our approach ignores the role of capacity constraints in isolating quasi-experiments embedded in the centralized assignment process, we compare estimates from our approach to one that isolates the quasi-experimental RD-like variation but is less flexible in studying selection patterns (Abdulkadiroğlu et al., 2022). Reassuringly, we find similar, albeit noisier, results. Thus, we use our framework to estimate major impacts on earnings and fertility and subsequently study their influence on gender differences in college major choice.

Using administrative employer-employee data, we document sizable gender differences in both major returns and self-selection patterns, highlighting the relative importance of each margin. Across the board, we find that men and women are rewarded differently for completing similar degrees, with women experiencing earnings gains less than men across all fields except Social Sciences, Teaching, and Humanities. The mean return differences are affected by a confluence of factors, including but not limited to labor market discrimination and firm and occupational sorting, which we explore later in the paper. With measures of preference intensity, we find that match effects are empirically important, indicating that students tend to sort in ways that are consistent with increasing earnings potential. As in Kirkeboen et al. (2016), but through a different empirical lens, we find that individuals with larger preferences for a given field tend to earn more if they do indeed earn a degree in that field of study. Gender differences in match effects are sizable for some majors (i.e., Science) and negligible for others (i.e., Engineering), an important component of the gender gap that was—to the best of our knowledge—previously undocumented.

Our comprehensive data allows us to study the dynamics of the gender gap in a similar spirit to Bertrand et al. (2010) with the additional margins we focus on. First, we focus on the relative contributions of differences in average returns and match effects to the within-major earnings gap and how that evolves over time. This analysis demonstrates that most of the within-major earnings gaps are due to differences in how men and women are rewarded for majoring in identical fields, although match effects play a non-negligible role in a few fields such as Law and Medicine. Importantly, this initial decomposition exercise suggests that within-major residual earnings gaps would persist if policies that reallocate women into high-earning fields were implemented. As for dynamics, we find that women face an immediate sizable gap upon graduation with a modest gradient into fourteen years post application. This evidence points to an immediate effect potentially governed by differences in occupational sorting, bargaining, and firm sorting. Our data are equipped to assess the role of firm sorting and that is the focus of the next decomposition.

Since Abowd et al. (1999), several researchers have emphasized the growing importance of firms in explaining earnings inequality (Card et al., 2016, 2018, 2013). In this spirit, we estimate a standard worker and firm fixed effects model from which we recover firm earnings premiums.[2] Equipped with these estimates, we study how much of the within-major gender gap is attributable to differences in firm premiums, or in other words, gender differences in firm sorting (Gallen et al., 2019). To begin, we find that major return differences partly operate through differences in access to firms with varying firm premiums; Engineering graduates, for example, gain access to firms with larger firm pay premiums than do Humanities graduates. Our estimates suggest that firm sorting explains nearly all of the gap for some majors but also nearly none for others. Turning to the dynamics of the within-major gap and its relation to differences in firm sorting, we find that in Science, for instance, the firm premium gap is half of the overall gender earnings immediately after college graduation, but this firm premium gap vanishes over time and becomes close to zero fourteen years after college application. In contrast, Engineering exhibits sizable and stable gender gaps in firm premiums. Across the board, however, we find that a modest share of the within-major gap is mediated by differences in firm pay premiums.

While a focus on the pecuniary returns to majors follows from the perspective that education is an investment (Becker, 1964), different fields of study expose students to vastly different peer groups, job opportunities, and geographic mobility (Barrios Fernández et al., 2021, Zimmerman, 2019). While those may be perceived as intermediate outcomes affecting the returns to particular fields of study, these factors are also key determinants affecting marriage and fertility decisions. There is ample evidence documenting a link between education, fertility, and marriage due to a host of reasons (Bertrand et al., 2021), so it follows that these anticipated factors influence educational decisions (Kuziemko et al., 2018). In this regard, we find that women experience positive fertility impacts from low-earning majors where they have disproportionate representation, such as Teaching and Health, and experience negative fertility impacts in high-earning male-dominated fields, such as Engineering. This evidence alludes to the potential difference in importance men and women assign to earnings and fertility at the college major choice stage. We present suggestive evidence that women prioritize fertility impacts over earning impacts compared to men, as captured by multivariate relationships between estimated major- and cell-specific mean utilities and our estimated fertility and earnings returns. This evidence indicates that these anticipated impacts generate rifts in the educational and labor market trajectories of men and women before they enter the labor market, potentially driven by gender norms (Akerlof and Kranton, 2000).

In the final part of our paper, we assess the impact of feasible policies that policymakers can use to address gender gaps. It is challenging to change preferences, but settings with centralized assignment systems have the flexibility to change the assignment rules while taking preferences as given. We motivate our analysis with the prominent role that the underrepresentation of women in Engineering plays in explaining the overall gap and consider two policies affecting the allocation of Engineering seats. The first policy focuses on a gender-neutral increase in capacity across all Engineering programs, while the second policy holds the number of available

[2]Our estimates have patterns broadly consistent with findings in Europe (Abowd et al., 1999, Card et al., 2016, 2013) and the United States (Song et al., 2019).

Engineering seats constant and reserves a percentage of seats for female applicants. Throughout our analysis, we take preferences as given and use our estimates to predict counterfactual outcomes. We find that any gender-neutral increase in Engineering seats only exacerbates the Engineering representation gap and the overall gender earnings gap.[3] In contrast, policies that reserve even modest shares of Engineering seats to females lead to significant reductions in both representation and earnings gaps. The reduction in the representation gap is mechanical, while the reduction in the overall gap is primarily due to reallocating females to a higher-earning field coupled with a reallocation of males to relatively lower-earning fields while accounting for their probability of graduation. A comparison with equivalent counterfactual policies in other fields shows that quotas in Engineering, Business, and Science have the largest bite to reduce the gender earnings gap. It is worth emphasizing that while these policies can reduce the country-wide average gender earnings gap, substantial within-major earnings gaps would remain.

Importantly, our findings take currently stated preferences as given and do not speak to factors that drive differences in sorting patterns in terms of earnings potential. For example, if our estimates reveal that a particular gender has particularly high match effects in a certain field, that may be due to awareness of occupation-specific wedges between earnings and marginal products due to labor discrimination (Hsieh et al., 2019), or due to different valuation for work amenities such as flexibility, which in turn lead them to different labor market trajectories (Kleven et al., 2019). They may also reflect the fact that men and women bargain differently (Roussille, 2020), or face different cultural norms (Jayachandran, 2015). Evidence notwithstanding, we take the current environment as given and are able to quantify how a potential mixture of all these factors subsequently influences the observed allocation of men and women into fields of study and the link to subsequent earnings differentials. Our counterfactual analysis also takes these various factors as given and assesses policies that may be successful in reducing gender earnings gaps. Nonetheless, understanding the various factors listed above continues to be an important avenue for future research.

Our work contributes to the literature focusing on estimating the returns to college and college selectivity (Card, 2001, Dale and Krueger, 2002, Mountjoy and Hickman, 2021b), and to a growing body of work that pivots focus to the returns to field of study (Altonji et al., 2012, Dahl et al., 2020, Hastings et al., 2013, Kirkeboen et al., 2016). The recent interest in returns to fields of study is partly based on the fact that the dispersion in field returns is as large as the returns to college (Altonji et al., 2012, 2017), pointing to the potentially important role that major plays for the gender earnings gap among college graduates (Sloane et al., 2021). While a central component of this paper relates to estimating field-specific returns among college graduates, our analysis makes two additional contributions. First, we allow field returns to vary by gender to quantify differences in how the labor market rewards similar men and women who major in identical fields. Second, we leverage rich preference data to understand how preference heterogeneity interacts with match quality and, as a consequence, efficiency.

Our focus on quantifying the contribution of major choice to the gender earnings gap adds

[3]This finding is a consequence of the fact that roughly **33** percent of males list Engineering programs as their most preferred, while less than **10** percent of women do. Therefore, any gender-neutral increase in capacity results in a disproportionate increase in male representation, worsening the gender earnings gap through both return differentials within Engineering and a disproportionate reallocation of males to high-earning fields.

to a growing body of work that documents gender differences in major choice (Blakemore and Low, 1984, Bordon et al., 2020, Neilson et al., 2021, Turner and Bowen, 1999, Zafar, 2009). Blakemore and Low (1984) find that women tend to choose majors that are subject to less atrophy, reducing the costs of time away from the labor market for child care. Turner and Bowen (1999) also outline stark gender differences in major choice but point out that this could result from differences in preferences or from the "chilling" effect of past labor market discrimination. Zafar (2009) finds that women place relatively less weight on pecuniary outcomes that materialize in the labor market, underscoring the importance of how men and women self-select into majors regarding earnings potential. Likewise, focusing on a different margin, Bordon et al. (2020) finds that males apply to selective programs even when they are marginal candidates, while equally qualified female candidates tend to apply less often to these programs. Women's peer groups have also been documented as important determinants of major choice (Brenoe and Zolitz, 2020). While the prior literature documenting gender differences in major choice illuminates ways major choice can contribute to the gender earnings gap, they all invariably lack the scope to quantify how much that matters. Closer to our work, Neilson et al. (2021) study how majors facilitate or inhibit sorting into firms with large pay premiums. Like them, we assess the impact of major choice on labor earnings. In contrast to them, we implement a control function approach that allows us to speak to the role of comparative advantage.

Our work also contributes to an extensive literature that studies the gender earnings gaps and factors that contribute to it over the life-cycle (Blau and Kahn, 1994, 2017, Goldin, 1990, 2014a, Goldin et al., 2017, Sloane et al., 2021). A growing body of work has illuminated that women absorb a disproportionate share of child-bearing responsibilities, commonly referred to as child penalties (Kleven et al., 2019). Roussille (2020) recently highlights the importance of the ask-gap in relatively high-earning online labor markets. Goldin (2014a) further emphasizes the role that nonlinear pay structure with respect to hours among some occupations contributes to contemporary residual pay gaps, and gender differences in preferences for flexibility or stable hours stand out as an important factor today (Bolotnyy and Emanuel, 2022). The relatively recent attention paid to preferences has highlighted that even in gender-neutral pay environments, differences in preferences for workplace amenities, such as location and driving speed, can produce gender earnings gaps (Cook et al., 2021). Our work builds on these papers by focusing on choices and preferences early in the life-cycle: college entry. We quantify the importance of major choice in contributing to existing gender earnings gaps and study an environment where policymakers can work around these preferences and introduce policies to reduce gender earnings gaps.

Last, this paper contributes to a growing body of evidence studying the potential effects of affirmative action within centralized assignment systems. Sparked by Abdulkadiroğlu and Sönmez (2003), centralized assignment is an increasingly popular way of allocating seats in education markets, with Neilson (2021) reporting that at least 50 countries use centralized assignment. This increase has coincided with an increase in affirmative action policies implemented through adjusting priorities within a given system. Relative to recent work (Ellison and Pathak, 2021, Otero et al., 2021), we pivot the focus to gender-based affirmative action and study the potential of such policies in reducing gender earnings gaps among college graduates.

An advantage of our counterfactual analysis is that it leverages known and transparent algorithms to simulate allocations, ameliorating concerns related to the role that modelling decisions could play in our results.

The rest of this paper is organized as follows. Section 2 outlines the institutional setting and describes the data we use; Section 3 outlines the potential outcome model and the model of major choice that our analysis rests on; Section 4 presents our baseline results and decomposes the gender earnings gap in various ways; in Section 5 we turn to assess various counterfactual assignment policies and their impact on the gender earnings gap; and last, in Section 6 we conclude.

2 Institutional Background, Data, and Descriptive Statistics

This section presents background information on Chile and its centralized college admission system. We then discuss the data generated by the college admission system along with the linkages that help facilitate our analysis. We conclude with descriptive evidence regarding trends in gender gaps and college major sorting that motivate our analysis.

College Admissions in Chile: Higher education admissions are based on high-school GPA and students' test scores at nationwide entrance exams. High school graduates can register once per year to take this national admission test (Prueba Selección Universitaria, PSU), an SAT-type exam with four sub-tests: Mathematics, Language, and the choice of taking Science or History. After receiving their scores, students can apply to a major and institution simultaneously (e.g., civil engineering, at the University of Chile). Each major-institution (a program) also ranks applicants by defining weights on the subject test scores and on the high school GPA. Institutions may impose additional eligibility requirements such as minimum scores.[4] Given students' rankings, program-specific scores, and capacities, the system offers students a seat at most one program so that no student-program pair prefers each other and is not assigned together. This is done using an algorithm built on Gale and Shapley (1962)'s student-proposing deferred acceptance algorithm. This process creates a cutoff for admission at each program, which corresponds to the score of the least qualified admitted student. Rejected students are entered into the waitlist for that program. After students decide whether to take the admission offer, waitlisted students might be offered admission in a second instance of the centralized admission system (see Rios et al. (2014) for details)

Important to our study are the facts that: i) when applying students must submit a rank-ordered list reflecting their preferences (they can rank up to ten college-major combinations), and ii) the nature of the process creates credible instruments from discontinuities that randomize applicants near unpredictable admission cutoffs. We leverage both of these features empirically to construct control functions that proxy for preferences for majors (Abdulkadiroglu et al., 2020) as well as to measure the risk of assignment of each student to different majors (Abdulkadiroglu et al., 2017).

[4] Two institutions, Universidad de Chile and Pontificia Universidad Católica de Chile have the additional requirement that majors must be ranked within the first four places. See Lafortune et al. (2016) for details.

Within the time frame of our study, the universities that used the centralized assignment mechanism were those belonging to a national council that grouped 25 institutions (Consejo de Rectores de las Universidades Chilenas, CRUCH). This council includes public and private universities. Selectivity varies among CRUCH universities but overall they are the most selective institutions, with programs requiring an average score in Mathematics and Language above the 45th percentile just to be considered for admission. Since 2012 more universities have become CRUCH members, and other non-CRUCH universities have adopted the centralized admissions system (see Kapor et al., 2020b for details).

Data: Our analysis combines rich administrative data on students' college applications, graduation, and labor market earnings. Data on college applications and admissions comes from the agency responsible for administering the national college entrance exam (Departamento de Evaluación, Medición y Registro Educacional, DEMRE). For all students who took the college admission exam, we observe their gender, high school, approximate geographic location, GPA, and test scores. These records include student-level data on demographics (gender, type of high school, approximate geographic location), performance (GPA and test scores), and rank-ordered lists of preferences for major institution pairs. Since our focus is on college graduates, we merge this data with the records of students' graduation that come from the Higher Education Information Service of the Education Ministry (Servicio de Información de la Educación Superior, SIES).

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*". To ease the exposition, we reclassify "*Social Sciences, Business and Law*" into three separate fields "*Social Sciences*", "*Business*", and "*Law*". We also separate "*Medicine*" from "*Health and Welfare*" and drop "*Agriculture*" and "*Services*" as they represent very few graduates (<5%) from non-homogeneous college programs in Chile. All in all, we end up with nine fields of study (see appendix A.2 for details.)

Labor market earnings come from the Chilean pension system (Superintendencia de Pensiones, SP), which administers the social contributions from all formal public and private labor relationships. While this is a universal, high-quality administrative dataset, it has two main limitations. First, it does not include the hours in the workers' contract. However, part-time employment is less common among college graduates than among other workers in Chile.[5] Second, wages are censored at the social security contribution limit. We address this issue by imputing wages above the limit as in Dustmann et al. (2009) and Card et al. (2013).[6] We complement the data from the Superintendencia de Pensiones with administrative records from

[5]According to the household survey CASEN 2017, only 8.6% of prime-age college graduates report to have worked part-time.

[6]Following see Gartner et al. (2005), We fit a series of Tobit models to log wages separately by gender, including the type of high school, financial-aid-relevant test-score ranges, and geographic controls. Then, we impute uncensored values for each censored observation using the estimated parameters of these models and random drawings from a truncated distribution (see Appendix A.1 for details.)

the Unemployment Insurance Administrator Agency (Administradora de Fondos de CesantÃa, AFC). This data only covers dependent labor relationships in the private sector but includes firm identifiers that we leverage to estimate a two-way fixed effects model to proxy for firm effects (Abowd et al., 1999, Card et al., 2013) and assess its role in accounting for gender gaps.

For our analysis, we focus on students who applied between 2004 and 2007 to college through the centralized admission system, who graduated from one field of study at most, and for whom we observe labor market outcomes in the formal sector. Table 1 presents descriptive statistics for individuals in our sample separately by gender and college major. There is much variation in the number of students, their average admission test scores, and demographics across genders and fields. Engineering has the highest number of male graduates, whereas Teaching and Health have the highest number of female graduates. Medicine is the most selective field, while Teaching is the least selective, but compared to Medicine, Teaching graduates come from a more disadvantaged background (e.g., less than 20% of their fathers have a college degree versus 50% of the fathers of graduates from Medicine). Across fields and genders, students from public schools and with public health insurance are significantly sub-represented.

Gender Earnings Gaps in Chile: We now present cross-sectional and time series evidence regarding gender gaps in Chile hat provides perspective and benchmarks our focal analysis.

We begin with a historical lens documenting trends in gender representation across majors and it's potential contribution to the overall gender gap. To do so, we use complementary publicly available data, the largest household survey in Chile (known as CASEN by its Spanish acronym). Respondents of the 2017 survey wave report their majors and wages, which allows us to decompose changes in the gap in a similar spirit as Sloane et al. (2021)'s analysis focusing on United States college graduates. Specifically, we construct a 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). Appendix Figure B.1 presents the across-cohorts evolution of both indexes. As in the US, majors in Chile have become less segregated over time. As shown by the panel (a), the similarity index increased from 0.55 for the 1960 birth cohort to 0.68 for the 1990 birth cohort, indicating that both genders are more evenly spread across majors for more recent cohorts.[7] Coupled with the improvement in gender integration, the earning potential of women has also increased over cohorts. Nonetheless, as shown by panel (b), women still have a lower earnings potential than males due to their sorting into lower-paying majors. Our estimates reveal a six percent gap attributable to differential sorting across majors.

Turning to more recent cross-sectional differences, Panels (a) and (b) of Figure 1 show the graduation and log average monthly earnings of the individuals in our estimation sample by gender and field of study. A salient fact from this figure is the "STEM gap" as men graduate disproportionally more from Engineering and Science, while females graduate disproportionally more from Health and Teaching, which are lower-paying fields compared to Engineering and Science. This suggests that the gender earnings gap might result from differences in preferences

[7]For the US, using the 2014-2017 American Community Survey, Sloane et al. (2021) reports that the same index increased from 0.55 for the 1950 birth cohort to 0.64 for the 1990 birth cohort.

for fields of study. Nonetheless, women also tend to earn less than men in high-earning fields like Medicine, Engineering, Science, and Law.

To assess the role of differential sorting compared to differential labor market returns, we decompose the gender earnings gap among college graduates in Chile. For this purpose, let μ_j^g stand for the average earnings of individuals of gender g who graduate from major j, and let s_j^g stand for the share of individuals that graduated from field j among those of gender g. Using this notation, we can decompose the overall earnings gender gap among college graduates $\mathbb{E}[\text{Earnings} \mid \text{Female}] - \mathbb{E}[\text{Earnings} \mid \text{Male}]$ into differences in sorting across fields of study and differences in returns within fields of study:

$$\sum_j s_j^F \mu_j^F - \sum_j s_j^M \mu_j^M = \underbrace{\sum_j (s_j^F - s_j^M)\mu_j^F}_{\Delta\text{Representation}} \quad + \quad \underbrace{\sum_j s_j^M (\mu_j^F - \mu_j^M)}_{\Delta\text{Returns}} \tag{1}$$

The first term of equation (1) captures differences in sorting patterns holding earnings constant; thus, it represents the share of the gap driven by the fact that men and women graduate from different fields of study. The second term holds the sorting patterns constant to capture within-major earnings differences, which may be driven by labor market factors disproportionately affecting women, such as discrimination, child penalties, or differential firm sorting. Figure 2 presents the results from this exercise that decomposes the gender earnings gaps—which corresponds to 19.2% ($4,758 USD per year in favor of men)—into these two components. We see that Engineering and Science are the main contributors to men's higher earnings, but this is mostly due to the low representation of females in these fields. In contrast, the higher representation of females in Teaching and Health, fields with equal returns to males and females, improves the earnings gap.

Two important takeaways from our descriptive decomposition are that the representation component is sizable, accounting for 82% of the gender earnings gap, and that the underrepresentation of women in high-earning fields such as Engineering and Science is an important channel explaining the overall earnings gap. These stylized facts point to policies that can affect the allocation of students to fields of study, which in many settings, including Chile, are much more feasible given centralized assignments (i.e., policymakers have more control over s_j^g in the sense that varying priority structures allow policymakers to address the portion of the gap driven by across majors representation gaps). However, the scope such policies can have in reducing the gender earnings gap hinges on the extent to which there is excess demand among women and the potential influence of the mismatch hypothesis.

3 Conceptual Framework

One of the primary goals of our analysis is to study factors contributing to the gender earnings gap which requires us to estimate returns to different fields of study and their impact on fertility. Recent advances in the literature have proposed new ways of estimating treatment effects in systems with centralized assignment (Abdulkadiroglu et al., 2017, 2020, Kirkeboen et al., 2016). Our emphasis on studying potential reallocation policies necessitates a framework that allows us to simultaneously study arbitrary selection patterns in different fields of study and estimate match effects, which are important considerations in any reallocative policy. Our framework borrows extensively from (Abdulkadiroglu et al., 2020) adapted to the major choice environment.

Potential Outcomes: We index students by $i \in \mathcal{I}$ and majors by $j \in \mathcal{J}$. Majors influence outcomes $k \in \mathcal{K}$. Student i's potential k-outcome from majoring in field j is given by:

$$Y_{ij}^k = \Upsilon_j^k(X_i) + u_{ij}^k, \quad j \in \mathcal{J}, \quad k \in \mathcal{K}$$

with $E[u_{ij}^k] = 0$ by construction for $k \in \mathcal{K}$. Without loss of generality, we can represent potential outcome gains relative to an arbitrary major,

$$y_{ij}^k = Y_{ij}^k - Y_{i0}^k = \mu_j^k(X_i) + \psi_{ij}^k,$$

where $\mu_j^k(X_i) \equiv \Upsilon_j^k(X_i) - \Upsilon_0^k(X_i)$ and $\psi_{ij}^k = u_{ij}^k - u_{i0}^k$. This formulation allows for treatment effects of major j relative to major 0 to vary across students based on both observable characteristics $\mu_j^k(X_i)$ and unobservables ψ_{ij}^k.

Major Choice: While the potential outcome model aids our understanding along one important dimension of the gender earnings gap among college graduates, gender differences in the $\mu_j^k(X_i)$, it is unlikely those are the only sources. As highlighted in Figure 2, differences in the representation of men and women in high-earning fields explain a majority of the gap; this is also true in other developed countries such as the United States (Sloane et al., 2021). This observation motivates us to focus on modeling demand for majors in a parsimonious way, abstracting away from demand for particular programs or institutions. This approach allows us to simultaneously model selection into majors and study rich sources of treatment effect heterogeneity captured by the ψ_{ij}.

We model student i's indirect utility from majoring in field j as,

$$U_{ij} = \sum_{k \in \mathcal{K}} \rho_{c(i)}^k \Upsilon_j^k(X_i) + \lambda_{c(i)d} D_{ij} + \lambda_{c(i)p} P_{ij} + \nu_{ij},$$

where D_{ij} is the distance between student i's residence and their most-preferred program corresponding to major j, P_{ij} is the mean net price of field j, and ν_{ij} captures any remaining unobserved preference heterogeneity.[8] This model assumes students can forecast their mean potential outcomes, $\Upsilon_j^k(X_i)$, and take pecuniary and distance costs into account when choosing a major. There is also an explicit parameterization of preference heterogeneity with respect to observable attributes X_i aggregated into distinct cells $c(i)$.[9]

We impose a location normalization with respect to a major indexed by 0, so that

$$u_{ij} \equiv U_{ij} - U_{i0}$$

[8]Mean net price consists of both the mean sticker price of programs in field j and an individual's financial aid offering.

[9]The cells include 3 school types, 3 macro-regions, 3 financial aid relevant PSU ranges, and 2 genders.

$$= \sum_{k \in \mathcal{K}} \rho^k_{c(i)} \mu^k_j(X_i) + \lambda_{c(i)d} d_{ij} + \lambda_{c(i)p} p_{ij} + \eta_{ij}$$

where $d_{ij} = D_{ij} - D_{i0}$, $p_{ij} = P_{ij} - P_{i0}$, and $\eta_{ij} = \nu_{ij} - \nu_{i0}$.

Related to financial aid and net price, students in Chile face different financial aid schedules governed by rigid discontinuities in the PSU distribution. We account for this in our choice of cell strata, which include different non-overlapping PSU score groups. Therefore, we assume that the net price students face, summarized by their PSU score, is constant within a cell. This allows us to summarize the mean utility for major j among those in cell c as

$$\delta_{jc} = \sum_{k \in \mathcal{K}} \rho^k_{c(i)} \mu^k_j(X_i) + \lambda_{c(i)p} p_{jc(i)}.$$

The empirical indirect utility specification is therefore

$$u_{ij} = \delta_{jc} + \lambda_{c(i)d} d_{ij} + \eta_{ij}.$$

Following standard assumptions in the discrete choice literature, we assume that any remaining unobserved preference heterogeneity, η_{ij}, which also subsumes match effects in the potential outcome model, has an Extreme Value Type 1 distribution (with draws that are independent conditional on δ_{jc} and d_{ij}).

Earnings and Fertility Impacts: Thus far, we have abstracted away from the elements of $\mathcal{K}$. There is an extensive literature documenting heterogeneity in returns to majors (Altonji et al., 2012, Hastings et al., 2013, Humlum and Meyer, 2022, Kirkeboen et al., 2016, Lovenheim and Smith, 2023), so we build on this literature in our analysis. There is concurrent literature studying how education affects fertility (Allison and Ralston, 2018, Brand and Davis, 2011, Breierova and Duflo, 2004, McCrary and Royer, 2011), which has natural implications for major choice and is also a focus of our analysis.

While the connection between majors and earnings follows from canonical human capital models that view education as an investment with pecuniary returns (Becker, 1964), the connection between major choice and fertility is more subtle. There is mounting evidence that identity is an important determinant of choices (Akerlof and Kranton, 2000, Bertrand, 2011, 2020, Bertrand et al., 2015, Goldin, 2006) and given the disproportionate child-bearing and nurturing responsibility attributed to women relative to men, it is likely there are gender differences in the importance assigned to fertility at this pre-labor market stage of life. Recent empirical evidence regarding the so-called child-penalty further points to the importance of anticipated fertility influencing educational decisions (Kleven et al., 2019, Kuziemko et al., 2018). Although existing literature has alluded to this link, there is scant evidence relating preferences to both anticipated earnings and fertility impacts. We shed light on this empirically by empirically assessing the relationship between preferences and earnings and fertility impacts. Through the lens of the model, we relate cell-specific mean-utilities with cell-specific returns

$$\delta_{jc} = \rho_c \bar{Y}^E_{jc} + \rho_c \bar{Y}^F_{jc} + e_{jc}.$$

Estimates of ρ^E and ρ^F yield insights about the importance of earnings and fertility in shaping major choice decisions. This exercise depends on mean outcomes of major j graduates for each cell c, which in turn depend on causal estimates $\mu_j(X_i)^E$ and $\mu_j(X_i)^F$.

Identification of Returns: Our empirical approach links potential outcomes to the choice model by allowing the unobserved preference heterogeneity to affect potential outcomes. For $j = 1, \cdots, J$ the potential k-outcome of student i is

$$Y_{ij}^k = \underbrace{\alpha_j^k + \beta_j^k G_i + \gamma^k X_i}_{\Upsilon_j(X_i, G_i)} + \underbrace{\sum\nolimits_r \psi_r(\eta_{ir} - \bar{\eta}) + \psi_j^*(\eta_{ij} - \bar{\eta}) + e_{ij}}_{u_{ij}},$$

where the mean outcome, $\Upsilon_j(X_i, G_i)$, depends on gender G_i and other observables X_i. The unobserved idiosyncratic match effect, u_{ij} depends on the unobserved preference heterogeneity η_{ij} in an additively separable manner.

The ψ_k captures the selection in terms of earnings potential for students with larger stated preferences for major k. For example, if $\psi_k > 0$ then that means that applicants with a stronger preference for major k tend to earn more regardless of the major they actually match with. Similarly, ψ_j^* captures match effects, commonly referred to as *selection on gains* in these types of models (Abdulkadiroglu et al., 2020, Bruhn et al., 2023, Einav et al., 2022, Otero et al., 2021). In the case that $\psi_j^* > 0$, that means that students that both have a higher preference for major j and complete major j experience additional earnings gain, evidence of positive Roy (1951)-like selection. In contrast, if $\psi_j^* < 0$ then that is evidence of negative Roy (1951)-like selection. Abdulkadiroglu et al. (2020) demonstrate that the conditional expectation of observed outcomes Y_i is

$$E[Y_i|R_i, X_i, G_i, j(i) = j] = \alpha_j + \beta_j G_i + \gamma X_i + \sum_k \psi_k \lambda_k(X_i, G_i, R_i) + \psi_j^* \lambda_j(X_i, G_i, R_i), \quad (2)$$

where $\lambda_j(X_i, G_i, R_i)$ are control functions derived from rank-ordered choice data contained in R_i in combination with an extreme value type 1 (EVT1) assumption on the unobserved preference heterogeneity η_{ij}.[10] Therefore, with estimates of λ_j for each major j, we can estimate heterogeneous major returns.

Estimating the Choice Model: We leverage rich information contained in applicants' rank-ordered lists to estimate the parameters of the choice model that then allow us to construct the $\lambda_j(X_i, G_i, R_i)$. We rely on the fact that truthful reporting in the Chilean centralized assignment system is a weakly dominant strategy.[11] A student reveals field j as their most preferred if they list it at the top of their list, the next-stated field is their second preferred, and so on. Preferences are summarized by a vector $R_i = (R_{1i}, R_{2i}, \cdots, R_{j(i)i})$ where R_{1i} is the top-listed field and the length of the list $j(i)$ is allowed to vary across students.[12] Thus, under truthful

[10]See Abdulkadiroglu et al. (2020) for the analytic representations of these control functions.

[11]Chile uses a variant of a student-proposing deferred acceptance algorithm for seat allocation in which truthful reporting is a weakly dominant strategy.

[12]For example, some students rank a single field across their list, while others rank multiple fields.

reporting, students' top-ranked field satisfies:

$$R_{1i} = \arg\max_{s\in\mathcal{J}} U_{is}$$

while the remaining options satisfy:

$$R_{ik} = \arg\max_{s\in\mathcal{J}\setminus(R_{1i},\cdots,R_{k-1i})} U_{is}, \quad k > 1.$$

The EVT1 assumption allows us to express the likelihood of observing the major-specific rank-ordered list as follows:

$$\mathcal{L}(R_i|X_i) = \prod_{k=1}^{j(i)} \frac{\exp(\delta_{kc} + \lambda_{dc} d_{ik})}{\sum_{r\in R_i\setminus R_{1i},\cdots,R_{k-1}} \exp(\delta_{rc} + \lambda_{dc} d_{ir})}.$$

We estimate preference models separately for the 18 covariate cells defined above (i.e., 2 school types, 3 macro-regions, 3 financial aid relevant PSU ranges) via maximum likelihood to obtain a list of major-specific mean utilities.

One potential concern regarding our approach is potential deviations away from truthful reporting. As Fack et al. (2019) points out, some students may skip the impossible, or constrained list lengths may introduce other empirical challenges (Haeringer and Klijn, 2009). In our context, we may observe some students never ranking Medicine because their PSU score is far away from the cutoff, even though they may have a preference for Medicine programs. Estimating preferences under an *ex-post stability* assumption is an increasingly popular approach that circumvents these issues. There are several reasons why we choose not to use this approach in our main analysis. To begin, estimating demand is not our end goal, and our focus is to estimate returns to the field of study and field-specific match effects. This requires identifying the λ_j, which is complicated by the implicit extrapolations embedded in the stability assumption. Simply put, the λ_k are not identified for low-scoring students applying to fields of study that have high admissions thresholds, complicating the empirical analysis, even though we may observe students ranking these out-of-reach fields.

We adopt an approach that utilizes all of the information contained in each individual's rank-ordered list to construct individual-specific control functions, emphasizing that approaches that exclude sizable amounts of data do so at the potential cost of misspecifying control functions which are essential for identification in this setting. A reassuring finding in our setting is the statistically identical estimates derived from our approach and the more rigorous and compelling but less flexible RD-like approach of Abdulkadiroglu et al. (2017) and Abdulkadiroğlu et al. (2022).[13]

Estimation and Inference: After estimating preferences, we construct control functions

[13]The approach proposed by Abdulkadiroğlu et al. (2022) uses information about preferences and capacity constraints to recover asymptotic approximations to applicants' propensity scores derived from the multitude of quasi-experiments embedded in each centralized match. This constant effects framework allows for precise identification of major returns but is less flexible in terms of studying match effects, which are crucial in our setting. It is nonetheless reassuring that our average returns are statistically similar to the returns estimated in the other approach that explicitly leverages random variation in assignments generated by the centralized system.

for each student and each major and augment a model with these functions as controls. We must account for this estimation error introduced in the preference estimation in our inference for the α_j and β_j. We use a parametric bootstrapping procedure to account for estimation error in the first step. Concretely, for each cell c, we have an estimate of the asymptotic distribution of (δ_{jc}, λ_{cd}), which we can draw from in each bootstrap iteration. Therefore, for each bootstrap iteration, we sample from the estimated asymptotic distribution of (δ_{jc}, λ_{cd}), construct control functions, and estimate the model using ordinary least squares using the bootstrapped λ_k and other covariates in our empirical model. For each α_j, β_j, ψ_j, and ψ_j^* we report the mean estimate across bootstrap iterations with the mean of the standard error.

4 Returns to Fields of Study, Match Effects, and the Gender Gap

In this section, we begin by documenting patterns in our estimates of unobserved preference heterogeneity, summarized by the control function estimates. We then turn to our primary estimates of major returns and match effects that vary with gender. These estimates allow us to then characterize the share of the within-major earnings gap in terms of differences in how the labor market rewards men and women, governed by gender-specific mean returns, and idiosyncratic match effects governed by preference heterogeneity. We use these findings to then assess the role of firm sorting in explaining the within-major gap; do men and women differentially sort into firms with different pay premiums? If so, what share of the gender gap can be explained by firm sorting? We also focus on the potential role of anticipated parenthood by estimating major impacts on parenthood. With pairs of earnings and fertility impacts by major, we can assess the influence of these factors on demand for majors.

4.1 Gender Differences in Preferences

Our motivating evidence displayed in Panel (a) of Figure 1 and in Figure 2 demonstrates that men and women exhibit differences in field of study preferences. The evidence there corresponds to realized outcomes, which depend on a sequence of outcomes including application, persistence, and graduation. A richer perspective on the preferences of applicants is through the lens of the control function estimates which summarize the unobserved preference heterogeneity embedded in applicants' rank-ordered lists.

Figure 3 reports a series of bivariate control function estimate correlations. Panel (a) focuses on control function correlations for females, and Panel (b) demonstrates similar correlations for males. The evidence is consistent with anecdotes and other leading empirical findings (Altonji et al., 2012, Kirkeboen et al., 2016). For both males and females, applicants with larger estimated unobserved tastes for Medicine also have larger tastes for Health programs, but have less intense preferences for Social Science or Humanities programs. Similarly, we find that both males and females with larger tastes for Social Science have larger tastes for Humanities and Law, but have less intense preferences for Science and Engineering. The evidence is also consistent with descriptive evidence documented in Appendix Figure B.2 reporting fallback major prevalence. Overall, the measures of preference intensity, also referred to as control functions in our analysis, recover reasonable preference heterogeneity consistent with findings in several other settings including our own.

Appendix Figure B.2 provides perspective on an important margin contributing to the gender earnings gap, gender differences in fallback prevalence. Among applicants ranking high-earning majors at the top of their lists, men and women may differentially list fallback options with varying earnings potential. For example, among applicants who rank Engineering at the top of their list, roughly half of males only list Engineering in their entire list in contrast to roughly 35 percent of females. The opposite is true for a more common female major, such as Teaching, where 45 percent of females only list Teaching programs while only 35 percent of males do the same. Among Engineering applicants, females are twice as likely as males to report Humanities as a fallback option. Given the evidence in Figure 1, it is much more common for female engineering applicants to marginally miss admission into their most preferred Engineering program and fall into a substantially less lucrative major. The differences in preference intensity, however, do provide some suggestive evidence that quota-like policies that reserve seats for women in Engineering may prove to have minimal impacts on efficiency as displaced males are more likely to remain in other Engineering programs, limiting the potential earnings loss. At this point, this is speculative and suggestive, but in the following sections, we provide rigorous evidence to explore this possibility.

4.2 Gender Differences in Returns and Match Effects

Table 2 reports estimates of gender-specific major returns and match effects; Panel (a) focuses on average returns and match effects for women and Panel (b) focuses on the same for men. The reference major is Health, a major that encompasses health education that excludes medical doctors and dentists, both of which are included in the Medicine category.

Across the board, we find that men and women experience differences in returns with most estimates precisely estimated; six of eight pairs of differences are distinguishable from statistical noise at conventional levels. Medicine is, by far, the field of study with the highest returns, with men experiencing a 50 log point increase in average monthly earnings and women a lesser but still sizable increase of 36 log points. Business, which tends to be associated with elite career paths in Chile (Zimmerman, 2019), is also a field of study where both men and women experience sizable returns. Again, however, women have a lower average return of roughly 22 percent in contrast to 29 percent for males. We also find sizable differences in returns to Engineering, the field of study whose differences in representation contribute most to the gender gap, with women experiencing a roughly 16 percent increase in earnings and males with an average return that is almost double that amount. The two majors in which returns are negative relative to Health, Social Science and Humanities, are the ones where women exhibit larger returns than men. Gender differences in returns inform about one dimension of the gap, but match effects can have diluting or amplifying effects.

We find strong evidence of selection on gains in that students with larger estimated preferences for a given major also experience larger returns from that major compared to others with lower estimated preference intensity. This evidence is consistent with the growing body of work finding selection on potential earnings gains in higher education settings (Kirkeboen et al., 2016, Otero et al., 2021). In contrast to mean return estimates, we find limited evidence of gender differences in match effects; only two of eight pairs of match effects are statistically different and they correspond to traditionally low-paying fields of study, Teaching and Humanities. Evidence notwithstanding, we do find some differences in match effects even though they may be indistinguishable from statistical error. For example, compared to the average student who obtains a Law degree, a woman whose unobserved preference heterogeneity index (the control function) is one standard deviation larger has a return that is 2.9 percentage points larger. For men, we find that increase to be 5.8 percentage points. In the case of Law, gender differences in match effects have an amplifying effect on the gender gap. The opposite is true for Engineering, where women's estimated match effects are larger although we cannot rule out that the differences are due to noise. For medicine, we find evidence of selection on gains for both men and women but match effects have a neutral impact on the within-major gap.

The match effect estimates tell us about direction of the diluting or amplifying effect, but they do not precisely quantify the relative importance of the match versus return channel. This is because men and women exhibit differences in intensity of preferences for field of study. Figure 4 sheds light on the relative importance of the return and match effect channel over time. Each subfigure reports the within-major gender earnings gap in blue, the portion of that gap due to differences in average returns, α_j, in red, and the portion due to differences in realized match effects, $\psi_j^* \times \lambda_j$, is reported in yellow. We report these contributions for a total of eight years, starting with seven years after applying to college and ending with 14 years post-application.

Figure 4 provides perspective on the dynamics of the gender earnings gap among graduates in the various fields of study we consider. Bertrand et al. (2010) find that the gender earnings gap among MBA graduates from an elite business school is minimal in the immediate years after graduation, with the gap growing larger over time as child-bearing years and responsibilities differently affect the decisions of men and women. Similar dynamics could be at play for Chilean college graduates, a setting where the average initial mothering age is 23 years old. In contrast to Bertrand et al. (2010), however, we find basically immediate gaps with remarkably small gradients between seven to fourteen years after initial application. This time window likely encompasses numerous job transitions where anecdotes and evidence suggest men and women make vastly different decisions in terms of occupations (Sloane et al., 2021), bargaining (Roussille, 2020), and firm sorting and bargaining (Card et al., 2016). We return to these points after our discussion about dynamics in the gap for the various factors considered in our analysis, namely match effects and average returns.

Besides a few minor cases, match effects play a minimal role explaining the within-major gap. It is perhaps not surprising that differences in match effects are not that large of a contributing factor to the within-major earnings gap given the evidence in Table 2. It is worth mentioning that the evidence in that table only reports differences in estimated ψ_j^*, while the evidence in Figure 4 reports gender differences in $\psi_j^* \times \lambda_j$. Therefore, our decomposition captures differences in both returns to preference intensity and gender differences in average preference intensity, finding that accounting for both margins still yields relatively small contributions to the gender earnings gap.

The main culprit driving the earnings gap for essentially all majors are differences in the

α_j, which is indicative of men and women obtaining differential rewards in the labor market. Differences in the α_j can occur for a host of reasons. Some reasons are out of one's control, such as discrimination or the non-linear returns to hours (Goldin, 2014a). Others, as discussed above, involve systematic differences in how men and women sort into firms and potentially negotiate (Card et al., 2016, Roussille, 2020). A growing body of work has documented the importance of firms in contributing to earnings inequality around the world (Abowd et al., 1999, Card et al., 2013, Song et al., 2019), which has natural implications for the gender gap. In the next section, we quantify the contribution of firm sorting in driving some of our initial findings.

4.3 The Role of Firms

Sector and firm-specific premiums account for a sizable share of earnings inequality (Card et al., 2018, Katz and Murphy, 1992, Krueger and Summers, 1988) and occupational sorting plays an important role in explaining gender earnings gaps (Goldin, 2014b). Recent evidence from Chile also shows that firms can contribute to the gender earnings gap through the major choice of college admits (Neilson, 2021). Motivated by these findings, we explore the extent to which sorting of males and females into different firms can lead to wedges in the premiums they receive.

For this purpose, we use a secondary employer-employee dataset, from the Unemployment Insurance Administrator Agency, that includes employer identifiers and allows us to estimate firm pay premiums from an AKM model (Abowd et al., 1999, Card et al., 2013).[14] We estimate the model for the log annual earnings of all workers within the largest connected set, which includes 59,969,972 observations (8,588,072 workers and 757,698 firms between 2009 and 2019). As we did before, we compare gender-specific returns to fields of study but now in terms of the firm premiums that they command in the labor market. This amounts to estimating the same model used in our baseline estimates reported in Table 2, with our focus on using estimates of firm effects as the primary outcome.

Before turning to gaps in firm pay premiums, it is useful to note that majors impact the types of firms students can eventually sort into. Appendix Table **??** reports estimates analogous to those shown in Table 2 replacing the outcome variable with estimated firm pay premiums observed for workers in 2019. For example, Science graduates tend to sort into firms with estimated pay premiums roughly 12 log points above those of Health graduates. Conversely, Humanities graduates seem to gain access to firms with far lower pay premiums, ranging between 11 and 15 log points lower than comparable Health graduates. Appendix Table **??** also reveals that while men and women Engineering graduates may both gain access to firms with larger premiums, they nonetheless tend to sort into firms with different pay premiums. The gap in firm pay premiums ranges from ZZ log points to YY log points in the cross-sectional model based on 2019 labor market outcomes.

As before, we focus on the dynamics of the gap over the first fourteen years after college admission, and Figure 5 presents the results obtained from estimating Equation 3 for several years after students' high-school graduation. The figure shows the overall gap in earnings (blue

[14]The main reason we consider this data as secondary is that it does not include public sector employment, a sector particularly important in Chile for professionals in fields like Teaching and Health. Nonetheless, we report estimates analogous to those in Table 2 using these data in Appendix Table **??**.

bars) and the gap in firm premiums (red bars). Reassuringly, the blue bars demonstrate that the mean earnings gap in the AFC data is similar to that in the SP data used in our non-AKM analysis. The red bars quantify the share of the log earnings gap that is accounted for by differential sorting into firms with different pay premiums. Our results show substantial variation both across fields of study and over time. The estimates for Law and Social Sciences for instance suggest that females sort into higher-paying firms than males early after college but lose this sorting advantage as time goes by. The opposite happens in Science where males match with higher-paying firms early on but the sorting gap disappears over time. Teaching and Engineering are fields exhibiting more stable sorting patterns over time, with firm premiums benefitting women in the former and men in the latter. This result is somewhat consistent with the findings in Aguirre et al. (2020) showing that enrollment in Engineering increases the probability of employment at high-paying and male-dominated industries for men, but not for women. Across the board, however, it is evident that differences in firm sorting explain a sizable share in nearly all of the earnings gap for nearly all fields of study with a majority of employees in the private sector. Before turning to counterfactual analysis, we study how majors impact fertility and the relative importance of anticipated earnings and fertility impacts on choices.

4.4 Fertility Impacts

The conceptual framework in Section 3 allowed potential outcomes for earnings and fertility to vary across majors. In this section, we assess how majors affect fertility and then study the relationship between preferences and major effects on both fertility and earnings in the next section.

Table 3 reports major effects on fertility. As before, major effects are among graduates relative to graduates in Health majors who average almost one child twelve years after applying to college and are roughly age 30. Focusing on returns first, we find that Teaching and Business major trajectories lead to higher fertility among women relative to Health majors. Teaching is the most common field among Female graduates, with nearly 30 percent of Female graduates in our sample obtaining a Teaching degree It is also among the lowest earning fields of study (see Figure 1). Conversely, Engineering, the major that is most male-dominated, leads to decreases in fertility impacts among women amounting to a roughly nine percent drop relative to Health graduates. The evidence, therefore, does suggest that there is a kernel of truth behind the notion that some women forego earnings in exchange for higher fertility down the line. These findings relate to Bursztyn et al. (2017) in that women may be apprehensive about signaling gender non-conforming behavior, exhibited through the choice of major, while in the dating market, a point we explore further in the next section. The unadjusted variance of fertility impacts for women is 0.15, an indication there is sizable variation across majors and suggesting it is a first-order concern at the major choice stage.[15]

Focusing on male fertility impacts, Panel B of Table 3 demonstrates similar sizable heterogeneity with an unadjusted variance of major effects equal to 0.14. The fertility impacts are statistically similar to that of females for Law, Science, Engineering, and Medicine. Where

[15]It is also important to note that the heterogeneity in major impacts on fertility is as large as the impacts of going to college, mirroring the findings from Altonji et al. (2012) in terms of earning impacts.

there are differences, the fertility impacts on men tend to be more negative than females, a common finding in that males have children at relatively older ages (CITE). Although there is evidence of heterogeneity in match effects, we do not find evidence of gender differences along this dimension. Taking our earning and fertility estimates, we explore the relative importance of each for major choice in the next section.

4.5 The Importance Earnings and Fertility for Major Choice

The insight this section provides is empirical evidence regarding a hypothesized link between anticipated earnings and fertility that differentially influences the labor market trajectories of men and women (CITE). To do this, we relate estimates of mean utilities estimated with our choice model to the earning and fertility impacts of the previous two sections. This exercise allows us to assess the relative importance and predictive power of these different potential outcomes that applicants weigh when transitioning to higher education.

Table 4 reports preference estimates. Panel A demonstrates that both earnings and fertility are independently predictive of major choice. For example, a one standard deviation increase in earnings is associated with a 0.469σ increase in mean utility. Similarly, a one standard deviation increase in fertility (number of children twelve years after application) is associated with 0.413σ increase in mean utility. Both earnings and fertility are predictive of choices once we hold constant the other, with evidence suggesting applicants' demand is similarly elastic for both. Panel B studies gender differences in preferences and we find substantial gender heterogeneity. Men and women both are responsive to earnings and fertility implications of majors, with women exhibiting less responsiveness to earnings and more responsiveness to fertility than men. This holds for both univariate and multivariate versions of the preference models. Importantly, conditional on earnings, a one standard deviation increase in fertility is associated with a 0.489σ increase in mean utility for women. In contrast, holding fertility constant, a one standard deviation increase in earnings is associated with a 0.24σ increase in mean utility. These findings point to a potential rift in the educational trajectories of men and women partly driven by differences in the relative importance of fertility.

Existing literature has alluded to a host of reasons that contribute to the potential rift. In more recent years, there has been a growing body of evidence pointing to the importance of identity in shaping the decisions of men and women (Akerlof and Kranton, 2000, Bertrand et al., 2015, Bursztyn et al., 2017, Del Carpio and Guadalupe, 2022, Delfino, 2021). Our evidence suggests that men and women differentially prioritize fertility concerns, potentially due to differences in gender norms governing the importance of fertility. Conforming to the norm leads women to forego potential labor market earnings, leading to underrepresentation in male-dominated fields, which also happen to exhibit higher earning levels. Of course, this evidence is suggestive but does shed light on a potential identity-related channel that contributes to the overall gender earnings gap by affecting pre-labor market human capital investments.

Taking stock of our results, our analysis thus far reveals four facts that inform our counterfactual analysis. First, roughly four-fifths of the overall gender pay gap among college graduates is due to representation. Second, of the remaining fifth, differences in average returns explain a majority of the gap, and although we find strong evidence of sorting on earnings gains for both men and women, gender differences along this margin are not economically meaningful relative to other margins. Third, majors generate differences in average returns by offering graduates access to firms with vastly different pay premiums, but firms are not the entire story with remaining scope for the importance of occupational sorting (Cortes and Pan, 2018, Sloane et al., 2021). Fourth, we find that fertility impacts also vary across majors and that men and women differentially prioritize these impacts when choosing their college major.

These findings suggest two potential avenues forward to potentially narrow the gap among college graduates. The first involves the daunting task of changing preferences. While there is ongoing work that explores this possibility (Del Carpio and Guadalupe, 2022, Coffman, 2014, Coffman et al., 2023, Exley and Kessler, 2022), that is outside the scope of this paper. Given that the representation gap explains 82% of the overall gap, reallocative policies that shuffle students across different fields are a feasible approach in a setting with centralized assignments. This approach requires us to take preferences as given, avoiding the daunting task of changing preferences, and asks how much progress can be made if we make slight alterations to the rules of the assignment process in feasible ways.

5 Counterfactual Analysis

In this section, we use the estimated returns to different fields of study by gender together with the algorithmic nature of the admission system to evaluate the impact of different policies on the expected gender earnings gap. Shuffling students across fields of study necessitates estimating returns that vary flexibly by gender and that take into account potential mismatch effects, both of which our empirical analysis takes into account. As for policies, we consider two types of policies: capacity expansions and gender quotas, two commonly advocated policies in higher education settings.[16] Capacity expansions are a gender-neutral policy whose potential disparate impacts depend on the nature of preferences among the applicant pool, while quotas target certain groups by design that cause displacement of untargeted groups and have potential efficiency implications.

The Chilean college admission systems uses the Deferred Acceptance algorithm to assign students to programs. The algorithm uses students' rank order lists, students' test scores and GPA, programs' capacities and specific weights that create a weighted average score. In this section, we combine our knowledge of this admission system and policy relevant variations of the system together with estimated returns to fields of study to prospectively evaluate the potential impact of these policies on the earnings gender gap.

5.1 Comparing Counterfactual Assignments

The objective is to simulate student assignments under alternative capacities, and quota policies. The inputs of the simulation analysis are students' rank order lists ($\mathbf{R}$) and program specific weighted scores ($\mathbf{s}$), college programs' capacities ($\mathbf{q}$), the fraction of seats where women have

[16]Mention policies discussed in Chile (https://www.mineduc.cl/universidades-ofreceran-cupos-extra-para-mujeres-en-carreras-stem/, https://www.latercera.com/que-pasa/noticia/brecha-de-genero-39-universidades-entregaran-cupos-especiales-a-mujeres-en-carreras-cientificas/F4AJ4VDRPBBD3MS5QLR6UBEPCQ/) and perhaps look at other settings.

priority in each program (ω), and a match algorithm that is a function that takes as inputs the previous elements and outputs a vector of student assignments (ψ). In what follows, we keep students' rank order lists and scores constant so we omit them going forward. When introducing quotas, we modify the match algorithm to consider priority seats processing open seats first and then reserved seats.[17] Then, for a given capacity and quota policy $(\tilde{\mathbf{q}}, \tilde{\omega})$, we simulate the counterfactual assignment to programs $(\tilde{\psi})$. We combine these counterfactual assignments with our estimates in Table 2. Recall that the observed mean outcome Y_i is given by Equation 3, so that the observed mean outcome under counterfactual assignment $\tilde{\psi}$ is

$$\mu_{ij} \equiv \mathbb{E}[Y_i|R_i, G_i, \tilde{\psi}_{\mathbf{i}} = j] = \underbrace{\alpha_j + \beta_j G_i}_{\alpha_{jg}} + \sum_k \psi_k \lambda_k(G_i, R_i) + \underbrace{\psi_j^* \lambda_j(G_i, R_i)}_{M_{ij}}. \tag{3}$$

For individual i, their individual-specific treatment effect for going from baseline allocation ψ_0 to counterfactual allocation $\tilde{\psi}$ is

$$\begin{aligned}\mathbb{E}[Y_i|R_i, G_i, \tilde{\psi}_{\mathbf{i}} = j] - \mathbb{E}[Y_i|R_i, G_i, \psi_{0i} = j'] = & \underbrace{(\alpha_j - \alpha_{j'}) + G_i(\beta_j - \beta_{j'})}_{\Delta\alpha_i(\psi,\psi_0)} \\ & + \underbrace{\psi_j^* \lambda_j(G_i, R_i) - \psi_{j'}^* \lambda_{j'}(G_i, R_i)}_{\Delta M_i(\psi,\psi_0)},\end{aligned}$$

showing that any changes are due solely through reallocations driven by differences in returns and match effects. Therefore, with estimates of α_j, β_j, ψ_j, and ψ_j^* for each field of study j we are equipped to estimate counterfactual gender gaps and the various components. In particular, define the gender gap under allocation ψ as

$$\Delta(\psi) \equiv \mathbb{E}[Y_i|F, \tilde{\psi}] - \mathbb{E}[Y_i|M, \tilde{\psi}] = \frac{1}{|F|} \sum_{G_i \in F} \left[\sum_j 1(\tilde{\psi}_i = j) \mu_{ij} \right] - \frac{1}{|M|} \sum_{G_i \in M} \left[\sum_j 1(\tilde{\psi}_i = j) \mu_{ij} \right]. \tag{4}$$

Therefore, the change in the gender gap induced by a transition to policy allocation ψ' is

$$\Delta(\psi') - \Delta(\psi) = \frac{1}{|F|} \sum_{G_i \in F} \left[\Delta\alpha_i(\psi, \psi') + \Delta M_i(\psi, \psi') \right] - \frac{1}{|M|} \sum_{G_i \in M} \left[\Delta\alpha_i(\psi, \psi') + \Delta M_i(\psi, \psi') \right]. \tag{5}$$

We define the component of the change due to differences in average returns as

$$\Delta\alpha(\psi, \psi') = \frac{1}{|F|} \sum_{G_i \in F} \left[\Delta\alpha_i(\psi, \psi') \right] - \frac{1}{|M|} \sum_{G_i \in M} \left[\Delta\alpha_i(\psi, \psi') \right], \tag{6}$$

and the component due to differences in match effects is

$$\Delta M(\psi, \psi') = \frac{1}{|F|} \sum_{G_i \in F} \left[\Delta M_i(\psi, \psi') \right] - \frac{1}{|M|} \sum_{G_i \in M} \left[\Delta M_i(\psi, \psi') \right], \tag{7}$$

Equation 5, Equation 6, and Equation 7 are our focus in our counterfactual analysis. Equation 5 summarizes the overall impact of a given policy, while Equation 6 and Equation 7 zoom in

[17] See Dur et al. (2018) for the importance of precedence in the processing of reserved seats.

on the drivers of the overall effect. In particular, the latter assesses potential improvements or reductions in allocative efficiency with respect to preferences and earnings potential.

In practice, our estimates contain various sources of error we must take into account. To begin, the α_j, β_j, ψ_j, and ψ_j^* are estimated with error and affect inference for the gaps represented in Equations 5 to 7. We use the parametric bootstrap to account for this estimation error. To be precise, for each counterfactual policy $\tilde{\psi}$, we take 100 draws from the estimated asymptotic joint distribution of α_j, β_j, ψ_j, and ψ_j^* and re-run the match using the draw from each bootstrap iteration. This generates a distribution of aggregate level gaps and our inference is based on the bootstrapped distribution which explicitly takes into account the estimation error in our return estimates. Because our baseline estimates have a rather large degree of precision, the bootstrapped distribution is unsurprisingly tight. We report 95 percent confidence bands throughout but ignore its discussion due to our relatively precise estimates.

The Role of Graduation. The counterfactuals above implicitly assume students graduate if re-allocated to a different field of study. Such an assumption is too strong in the pool of all college applicants. In our sample of college graduates, it is more reasonable but we nonetheless probe at the robustness of the results. We train a Random Forest model to predict graduation in different fields of study using the host of factors in our analysis. The model has high predictive validity with forecast coefficients equal to approximately one across all majors and additional details are provided in Appendix E. We then allocate students with low graduation probability in their reallocated field as non-graduates and assign them the mean earnings of other similar non-college graduate students. We report a variety of estimates that vary the thresholds and allow us to assess the importance of the graduation margin relative to our preferred results. Therefore, our results account for potential mismatch effects of reassigning students to fields of study with low predicted graduation rates.

5.2 Counterfactual Outcomes

In light of our motivating evidence in Figure 2 finding that representation in Engineering is key for the overall gender pay gap, we consider the impact of different capacity expansion and quota policies in Engineering. In particular, we consider expanding all Engineering programs by 10%, 30%, or 50%. Similarly, we consider keeping capacities constant but reserving 10%, 30%, or 50% of seats for female students.

Table 5 summarizes representation gaps in Engineering and factors contributing to the overall gender pay gap under different capacity and quota policies. The first row presents the baseline assignment. The overall assignment gap in Engineering is 21.4 percentage points, with 40% of male students and only 18% of female students assigned to Engineering (among assigned students). Of the 15.6 log point gender gap, shown in Column (4), 83 percent of that gap is due to differences in returns aggregated across all students with the remaining 17 percent due to differences in match effects. The subsequent rows demonstrate how these different components and contributors to the gap change under alternative policies.

The second through fourth rows demonstrate that the assignment gap only gets worse as we consider capacity expansions of 10%, 30%, and 50%, increasing to 18.5 percent for a policy that increases Engineering seats for each program by fifty percent. As mentioned above, capacity expansions are a gender-neutral policy that disproportionately benefits men. Appendix Figure B.2 shows that this is likely due to differences in fallback options across gender. Nearly half of all men only rank Engineering programs on their rank-ordered lists and far more men rank Engineering to begin with, both facts indicating that excess demand for Engineering is greater among men. With that said, a seat expansion would surely produce more female engineers, but the nature of the policy can only exacerbate representation gaps and the overall earnings gap. Given the disproportionate excess demand among males, it is not surprising to see that the overall gender pay gap among college graduates increases by roughly three percentage points, amounting to a 18 percent increase from the baseline allocation. Most of this change is driven by increases in the gender gap in average returns, a feature due to males moving up from lower-paying majors to Engineering programs they failed to qualify for in the baseline allocation. Column (5) accounts for potential differences in graduation rates due to the reassignment and shows qualitatively similar results.

Although an across-the-board increase in Engineering seats does not do much to reduce the gender pay gap, the fifth through seventh rows of Table 5 demonstrate that gender-specific quotas can move the needle. As expected, we see that quota policies lead to mechanical reductions in the representation gap, reducing it between 8.5 and 33.5 percent depending on the quota. Despite the sizable gender gap in the returns to Engineering, a quota closes the gender earnings gap substantially. For example, a 10% quota decreases the Engineering assignment gap from 21.4 percentage points to 18.2 percentage points and reduces the gender earnings gap by 8.5 percent, down to 14.4 percentage points. A policy that would aim to equalize access to Engineering programs would still fail to eliminate the representation gap as there are not enough female applicants, but would nonetheless reduce it by 60 percent to 8.4 percentage points. And again, despite the fact that the mean Engineering return for women is roughly half of that of males, the overall gender earnings gap among college graduates reduces by 33.5 percent.

Although our motivating evidence in Section 2 suggested policies targeting Engineering would have the most bite, we also study how seat expansion and quota policies in other majors impact the gender earnings gap. Figure E.2 reports estimates of Equation 5 for various combinations of policies and majors. For example, the top panel considers how the gender gap evolves in response to a fifty percent seat expansion for each program in a given field of study. The vertical black line corresponds to the baseline gap we observe in our data. The sizable changes to the supply of programs considered in these counterfactuals tend to produce minimal impacts on the gender earning gaps, and as before, expansions in fields of study that are predominantly male tend to exacerbate the gap.

The bottom panel considers fifty percent quotas for different majors. The 33.5 percent reduction induced by a fifty percent engineering quota is by far the largest of all the policies that we consider.[18] While we observe non-negligible reductions for fifty percent quotas for other high-earning fields of study, they tend to be milder because the gender imbalance in *application* tends to be less severe. This latter point emphasizes that our estimates involve moving students

[18]Interactions of the two policies, not reported here, tend to produce mixed evidence. In general, the effect of a quota in a high-earning field tends to be offset by a companion seat expansion in that same field.

across majors that they report on their rank-ordered list and thus come from students who seriously consider these options in the first place.[19] This observation naturally begs a question about who benefits and who gets displaced, topics we explore in further detail in the next section.

5.3 Who are the women nudged into Engineering?

The counterfactual exercises document that there is scope to drastically reduce gender pay gaps in settings that use centralized assignments for allocating students to universities and programs. Our findings warrant further investigation and a more detailed characterization of affected students. In this section, we ask two questions. First, who exactly benefits, and how do they compare to typical Engineering applicants in the baseline allocation? Second, if there are enough women ranking Engineering programs on their applications that generate sizable reductions in societal-level gender earning gaps, why are they not getting in in the first place?

To answer the first question, Appendix Figure YY reports descriptive statistics comparing applicants affected by the counterfactuals.

One obvious answer to the second question is that there are potential gender differences in applicants' competitiveness based on their PSU scores which govern their competitiveness in programs. Appendix Figure E.3 sheds light on this possibility, demonstrating roughly similar distributions with more mass of male applicants at higher ends of the PSU distribution. Focusing on PSU scores alone misses importance pieces of the pie, however, as there could be gender differences in the competitiveness of programs that men and women apply to. Appendix Figure E.4 demonstrates that there is substantial heterogeneity in the types of Engineering programs that men and women apply to. Combining these two margins, Appendix Figure E.5 provides perspective on differences in distance to cutoffs among Engineering applicants. The evidence seems to suggest that men do a slightly better job targeting programs at which they are likely to clear the cutoff though, but these distribution plots do not quite isolate that phenomenon.

To do so, Figure 6 conditions on Engineering applicant PSU score and reports the mean cutoff score at their top-ranked program. The evidence clearly demonstrates that there are gender differences in ranking or reporting behavior across the entire PSU distribution. Panel (b) suggests that this phenomenon is slightly more pronounced among applicants whose fallback option is not an Engineering program. These female applicants are then likely to be allocated to lower-earning majors, suggesting that gender differences in reporting behavior among Engineering applicants are having a non-negligible impact on the representation gap. It is important to emphasize that these comparisons are among Engineering applicants and are not inconsistent with findings that show that men and women differentially list STEM and non-STEM programs conditional on PSU.

There are several potential interpretations of this phenomenon. One may be that women are risk-loving, but that would be inconsistent with an extensive body of evidence suggesting women are more risk-averse than men (Bertrand, 2011). While we are limited in what we can say in our data, survey findings in Fabre et al. (2021) show that women are slightly better

[19] Most students report X majors, so it is not the case that every student reports an Engineering program, for example.

at forecasting cutoffs but do much worse forecasting their admission probabilities than men. Combining these two facts suggests that risk-loving behavior is not driving the differences displayed in Figure 6, but instead, potentially slightly optimistic behavior in the admissions process. These findings underscore the importance of recent policies aiming to better inform students about the admissions process and address information frictions that undermine their success in centralized assignment systems (Arteaga et al., 2022, Kapor et al., 2020a). More generally, these findings provide the first evidence that gender differences in reporting behavior and information frictions in centralized assignment systems have important implications for other policy-relevant outcomes not previously considered, such as the gender earnings gap.

6 Conclusion

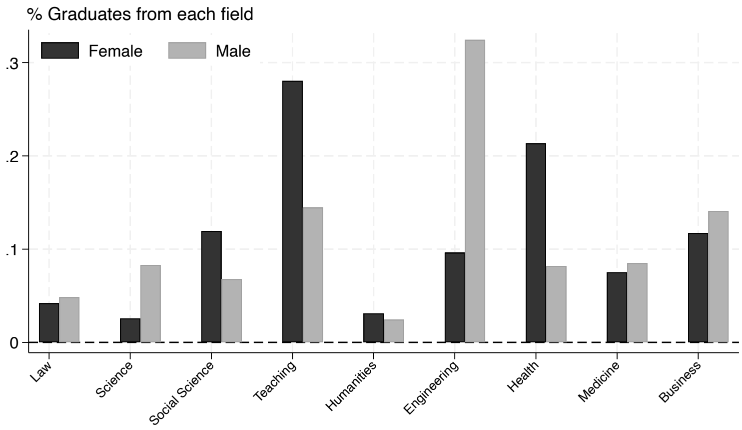
This paper studied the gender earnings gap in Chile, emphasizing the importance of differences in the returns to different fields of study for each gender for both pecuniary and non-pecuniary outcomes. This allows us to then assess the relative importance of each and the potential rifts they generate before individuals enter the labor market. Equipped with these returns, we study the potential impacts of feasible policies within centralized assignment systems.

To begin, we find that differences in representation in high-earning fields of study account for 82 percent of the raw 19.2 percent gender earnings gap among college graduates. We then show that even within majors, men and women accrue different returns across all fields of study. We focus on fertility as a non-pecuniary return that men and women may differentially weigh at the major choice stage and also find sizable heterogeneity in returns across fields of study. With both sets of estimates we then find that men and women differentially prioritize earnings and fertility, generating rifts in their educational trajectories during this pre-labor market decision. Because changing preferences is outside of the scope of this paper, we focus on feasible policies within centralized assignment systems.

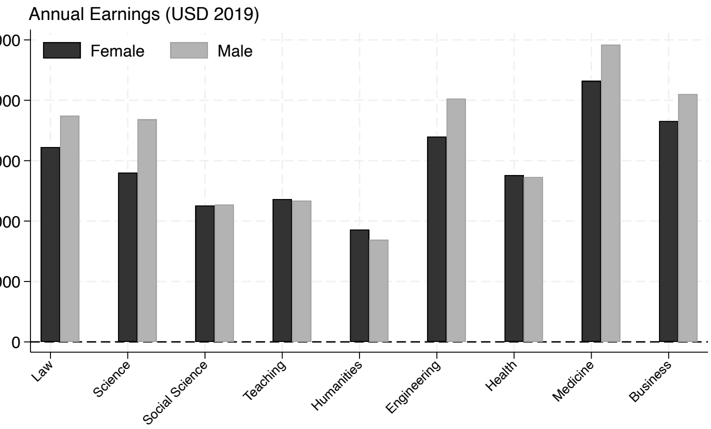
We find that gender-specific quotas lead to meaningful reductions in the gender earnings gap among college graduates, while expansions of capacities potentially exacerbate the gap. We also find minimal impacts on the implied efficiency of the centralized match. One explanation for this is due to a novel finding related to gender differences in reporting behavior in centralized assignment systems. The women who would benefit from quotas are women who rank more competitive programs than men, conditional on their PSU score. Therefore, the women that are nudged into Engineering are more qualified in terms of their PSU score but were hurt in the baseline match due to differences in strategic play during their interactions with the centralized match. This finding underscores the importance of information schemes that level the playing field at the application stage.

On a final note, it is worth cautioning that our findings take currently stated preferences as given and do not speak to factors that drive differences in sorting patterns in terms of earnings potential. Nonetheless, we find evidence that feasible policies in settings with centralized assignment systems can generate meaningful progress in narrowing the residual gap. Understanding the various factors that contribute to gender differences in preferences continues to be an important avenue for future research.

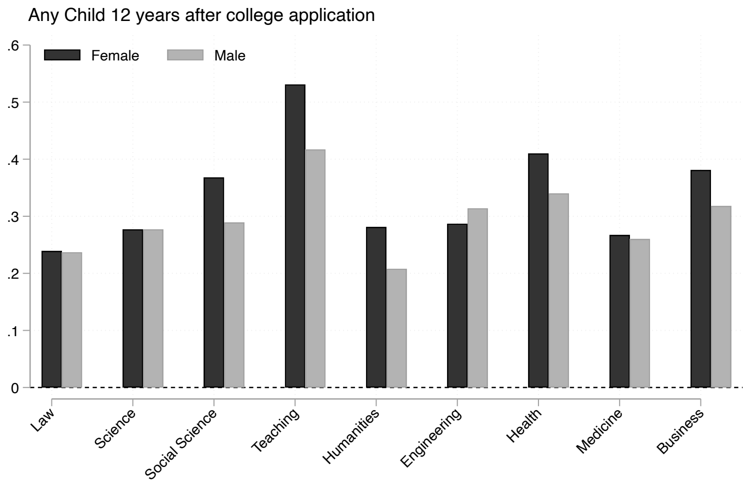
Figure 1: Graduation and Earnings



(a) Graduation



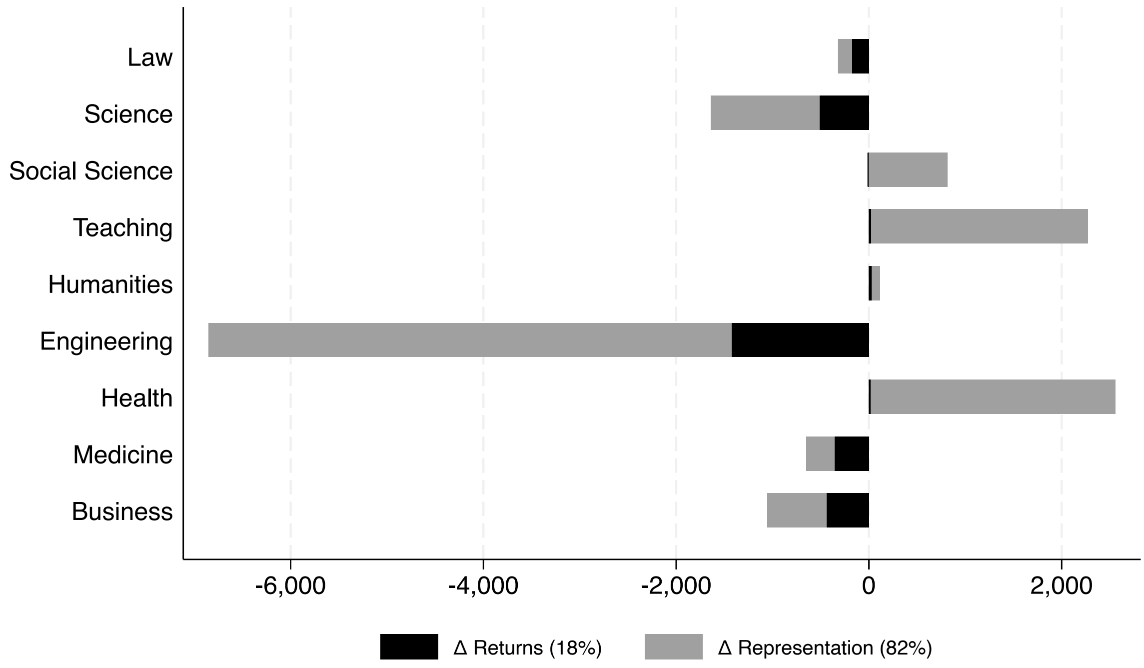
(b) Earnings



(c) Fertility

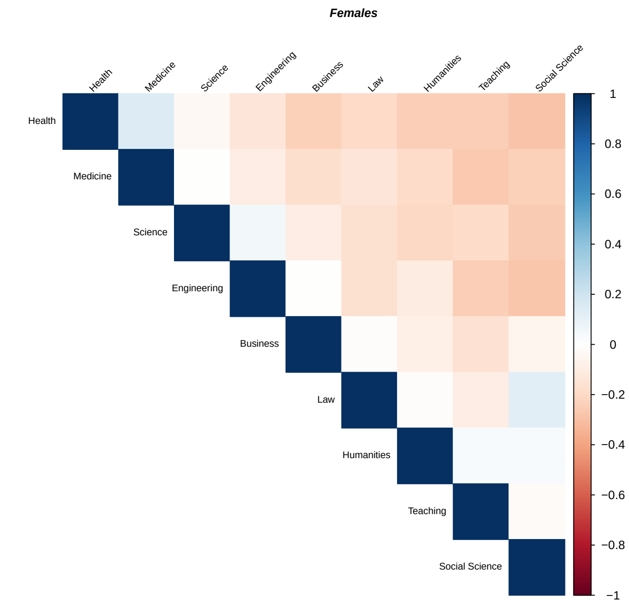
Notes: Panel (a) shows the share of male and female graduates in each field of study. Panel (b) shows the annual earnings (as of 2019) of male and female graduates in each field of study. Both panels consider students who applied through the centralized admission system between 2004 and 2007, graduated between 2007 and 2019, and were employed in 2019.

Figure 2: Earnings Gap: Sorting versus Returns

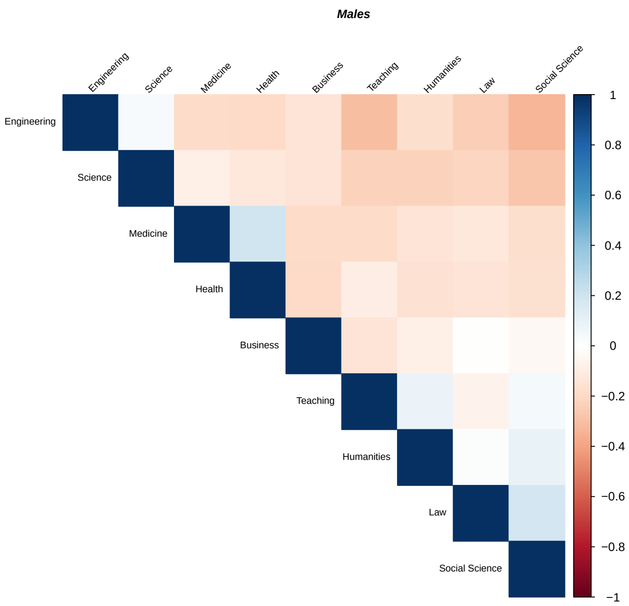


Notes: This figure shows the result from the exercise described by equation (1) that decomposes the gender earnings gap into differences in sorting between fields of study and differences in returns within fields of study. We consider the annual earnings in 2019 of students who applied through the centralized admission system between 2004 and 2007, graduated between 2007 and 2019, and were employed in 2019.

Figure 3: Pairwise Correlations of "Unobserved" Preferences



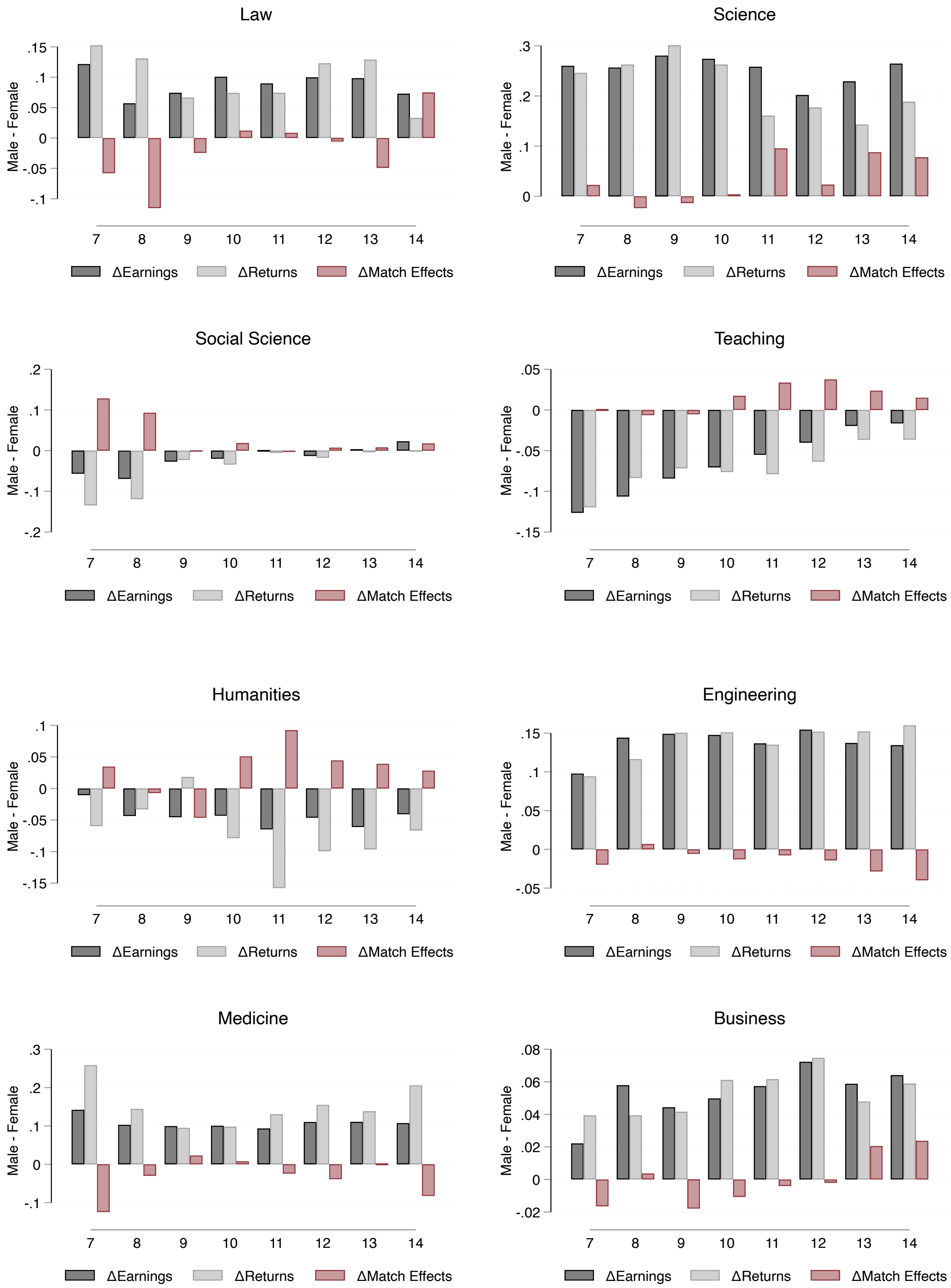
(a) Female



(b) Male

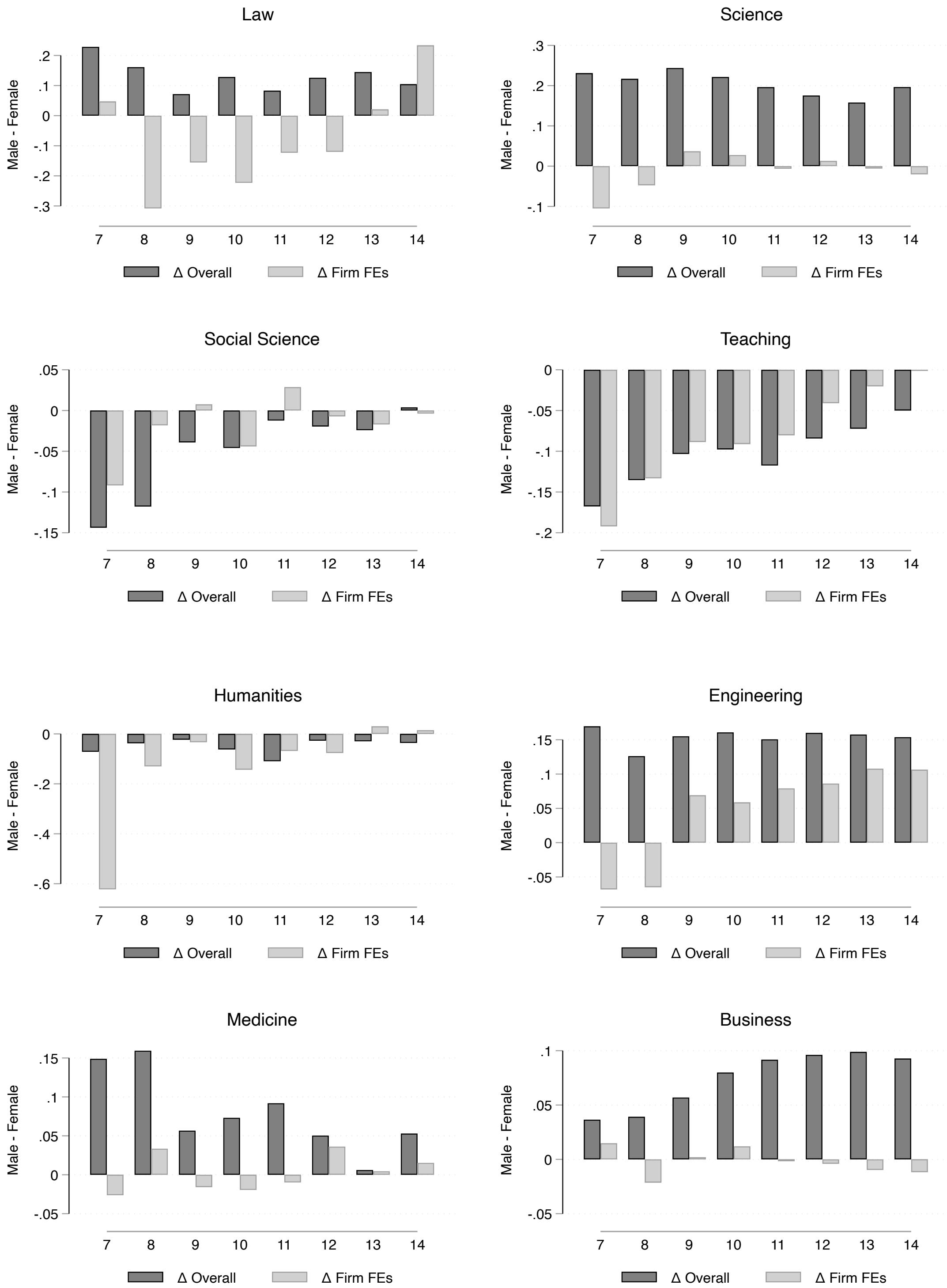
Notes: This figure shows the pairwise correlations between students' unobserved preferences for fields of study (as proxied by the control functions). Panel (a) shows the correlation matrix for unobserved female preferences. Panel (b) shows the correlation matrix for unobserved male preferences. We consider all students who applied through the centralized admission system between 2004 and 2007, graduated between 2007 and 2019, and were employed in 2019.

Figure 4: Gender Earnings Gap Over Time



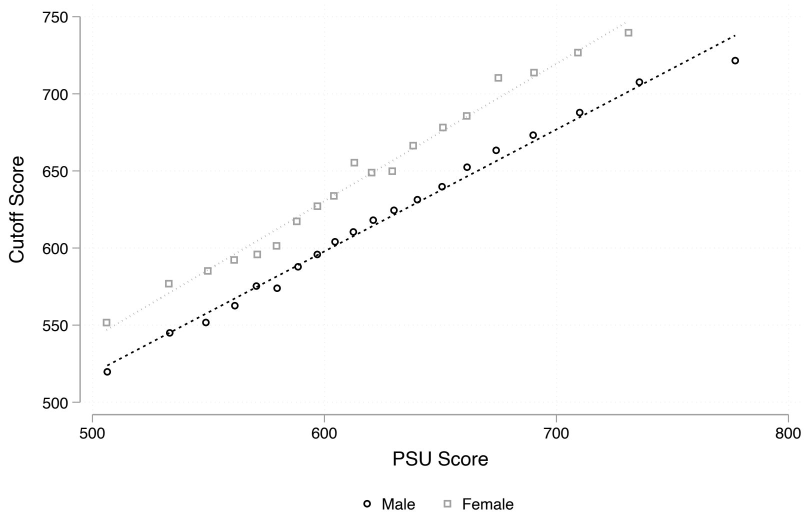
Notes: This figure shows the results obtained from estimating equation (3) using labor market earnings at different time horizons (after high school graduation) as the dependent variable. For each field of study, the figure presents the overall gender earnings gap and its components: the gender gap in returns and the gender gap in match effects. The gender gap in level effects is omitted. We consider all students who applied through the centralized admission system between 2004 and 2007, graduated between 2007 and 2019, and were employed at a given time horizon after they graduated from high school.

Figure 5: Gender Earnings Gap Over Time: The Role of Firms

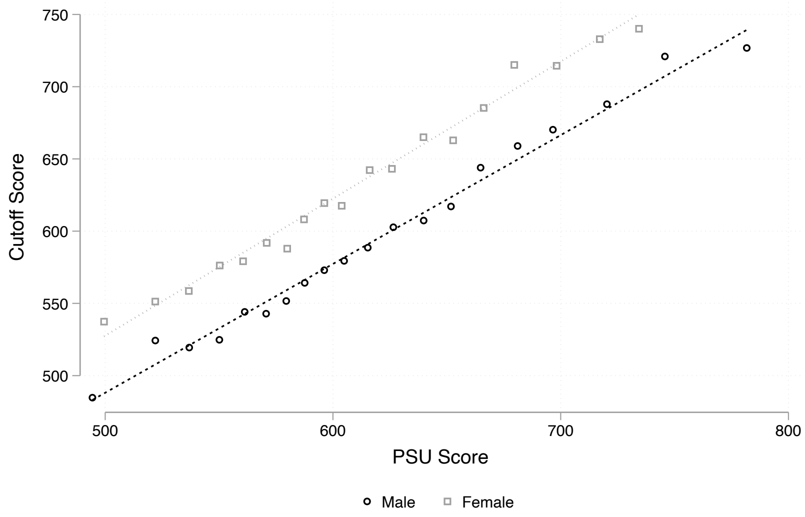


Notes: This figure shows the results obtained from estimating equation (3) using labor market earnings and firm premia at different time horizons (after high school graduation) as the dependent variable. We only consider workers in the private sector since firm identifiers are only available for them. For each field of study, the figure presents the overall gender earnings gap alongside the gender gap in firm premia (i.e., firm fixed effects estimated following Card et al. (2013); see Section 4.3 for details). We consider all students who applied through the centralized admission system between 2004 and 2007, graduated between 2007 and 2019, and were employed at a given time horizon after they graduated from high school.

Figure 6: Gender Differences in Application Behavior



(a) Any Fallback



(b) Non-engineering Fallback

Notes: Panel (a) plots the cutoff scores against applicant PSU scores for their top-ranked program. The sample is restricted to applicants who rank Engineering programs at the top of their rank-ordered list. Panel (b) is similar but restricts to the applicants who rank something other than Engineering as their fallback option.

Table 1: Descriptive Statistics

	Law (1)	Science (2)	Social Science (3)	Teaching (4)	Humanities (5)	Engineering (6)	Health (7)	Medicine (8)	Business (9)
					Panel A: Females				
College Admission Score (Z-score)	1.15	0.92	0.73	0.42	0.93	1.02	0.81	1.61	0.78
Father is College Grad	0.46	0.28	0.34	0.17	0.46	0.37	0.26	0.54	0.30
Mother is College Grad	0.41	0.24	0.29	0.13	0.38	0.29	0.22	0.47	0.24
Public Health Insurance	0.36	0.52	0.46	0.62	0.35	0.45	0.52	0.30	0.48
Public School	0.12	0.23	0.20	0.31	0.10	0.15	0.23	0.09	0.18
Observations	2,595	1,588	7,385	17,364	1,921	5,959	13,215	4,651	7,249
					Panel B: Males				
College Admission Score (z-score)	1.28	0.92	0.85	0.55	0.89	1.11	0.86	1.75	0.96
Father is College Grad	0.50	0.29	0.35	0.17	0.35	0.37	0.23	0.51	0.37
Mother is College Grad	0.43	0.23	0.30	0.14	0.28	0.29	0.20	0.44	0.28
Public Health Insurance	0.31	0.50	0.46	0.65	0.46	0.43	0.56	0.31	0.42
Public School	0.15	0.25	0.24	0.33	0.21	0.19	0.31	0.18	0.18
Observations	2,411	4,145	3,376	7,216	1,217	16,182	4,089	4,234	7,034

Notes: This table presents the average test scores and demographic characteristics of students in our main analysis sample by gender and field of study. Our main analysis sample includes all students who applied through the centralized admission system between 2004 and 2007, graduated between 2007 and 2019, and were employed in 2019.

Table 2: Gender Differences in Returns and Match Effects

Dependent variable: Log Monthly Earnings in 2019

	Law	Science	Social Science	Teaching	Humanities	Engineering	Medicine	Business
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Females				
Returns	0.041	0.022	-0.168	-0.004	-0.398	0.160	0.355	0.215
	(0.046)	(0.040)	(0.020)	(0.011)	(0.044)	(0.018)	(0.027)	(0.017)
Match Effects	0.029	-0.003	0.021	-0.006	0.048	0.047	0.011	0.039
	(0.016)	(0.021)	(0.010)	(0.007)	(0.016)	(0.012)	(0.012)	(0.008)
				Panel B: Males				
Returns	0.085	0.233	-0.229	-0.055	-0.517	0.316	0.501	0.299
	(0.054)	(0.026)	(0.029)	(0.014)	(0.048)	(0.015)	(0.032)	(0.018)
Match Effects	0.058	0.028	0.049	0.026	0.072	0.038	0.013	0.045
	(0.018)	(0.012)	(0.015)	(0.010)	(0.018)	(0.010)	(0.015)	(0.009)
Est. Females = Est. Males								
Δ Returns (p-val)	0.328	0.000	0.037	0.000	0.155	0.000	0.001	0.002
Δ Match Effects (p-val)	0.524	0.407	0.059	0.009	0.484	0.795	0.920	0.539

Notes: This table presents the estimates obtained from our main regression model, presented in equation (3), with health as the omitted field of study. We display the averages—of coefficients, robust standard errors, and p-values—across 100 regressions, each of which uses a different set of control functions obtained after parametric bootstrap over the ranked ordered logit estimation. The sample includes 111,831 observations of students who applied through the centralized admission system between 2004 and 2007, graduated between 2007 and 2019, and were employed in 2019.

Table 3: Fertility: Number of children 12 years after college application

Dependent variable: Number of Children

	Law	Science	Social Science	Teaching	Humanities	Engineering	Medicine	Business
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Females				
Returns	-0.197	-0.251	-0.068	0.139	-0.265	-0.079	-0.117	0.057
	(0.033)	(0.032)	(0.019)	(0.014)	(0.029)	(0.019)	(0.025)	(0.019)
Match Effects	0.036	0.001	-0.020	0.003	0.057	0.001	0.027	-0.009
	(0.012)	(0.016)	(0.010)	(0.008)	(0.011)	(0.013)	(0.012)	(0.010)
				Panel B: Males				
Returns	-0.234	-0.303	-0.295	-0.097	-0.487	-0.109	-0.128	-0.088
	(0.036)	(0.023)	(0.022)	(0.017)	(0.027)	(0.016)	(0.028)	(0.019)
Match Effects	0.023	0.011	0.000	-0.010	0.044	0.008	0.040	-0.015
	(0.013)	(0.011)	(0.012)	(0.011)	(0.011)	(0.010)	(0.013)	(0.009)
Est. Females = Est. Males								
Δ Returns (p-val)	0.439	0.169	0.000	0.000	0.000	0.172	0.745	0.000
Δ Match Effects (p-val)	0.466	0.600	0.178	0.354	0.422	0.658	0.435	0.671

Notes: This table presents the estimates obtained from our main regression model, presented in equation (3), with health as the omitted field of study. The sample includes 140,690 observations of students who applied through the centralized admission system between 2004 and 2007, graduated between 2007 and 2019. The mean of the dependent variable among Health graduates is 0.892.

Table 4: Preference Estimates

	(1) Utility	(2) Utility	(3) Utility
	Panel A: Pooled Estimates		
Earnings	0.469		0.349
	(.067)		(0.064)
Fertility		0.413	0.338
		(0.050)	(0.049)
	Panel B: Gender Heterogeneity		
Earnings	0.599		0.480
	(0.083)		(0.078)
X Female	-0.313		-0.238
	(0.110)		(0.096)
Fertility		0.276	0.154
		(0.068)	(0.067)
X Female		0.281	0.335
		(0.097)	(0.091)
Observations		288	

Notes: This table reports estimates from several regressions of estimated mean utilities on earnings and fertility among graduates at the cell-major level, where cells are defined as elsewhere in the paper. Column 1 reports estimates from bivariate regressions of mean utility on earnings and Column 2 reports analogous bivariate regression estimates of mean utility on fertility. Column 3 reports estimate of multivariate regressions of mean utility on earnings and fertility. Panel B reports similar estimates but further considers gender heterogeneity in preferences. All covariates are standardized to be mean zero with standard deviation equal to one. Standard errors are robust and reported in parentheses.

Table 5: Counterfactuals Admissions to Engineering

	Representation Gap	Return Gap	Match Effect Gap	Overall Earnings Gap	Overall Earnings Gap w/ Graduation
	(1)	(2)	(3)	(4)	(5)
Baseline	-0.214	0.1305	0.0193	0.1568	0.1630
		[0.1304 , 0.1307]	[0.0192 , 0.0194]	[0.1567 , 0.1568]	[0.1630 , 0.1630]
10% Increase in Capacity	-0.221	0.1369	0.0199	0.1641	0.1664
		[0.1368 , 0.1370]	[0.0198 , 0.0200]	[0.1640 , 0.1641]	[0.1663 , 0.1664]
30% Increase in Capacity	-0.233	0.1493	0.0208	0.1779	0.1699
		[0.1492 , 0.1495]	[0.0207 , 0.0209]	[0.1778 , 0.1780]	[0.1699 , 0.1700]
50% Increase in Capacity	-0.239	0.1556	0.0212	0.1851	0.1732
		[0.1555 , 0.1558]	[0.0211 , 0.0213]	[0.1850 , 0.1852]	[0.1732 , 0.1733]
10% Quota for women	-0.182	0.1187	0.0184	0.1437	0.1589
		[0.1186 , 0.1188]	[0.0183 , 0.0185]	[0.1436 , 0.1437]	[0.1588 , 0.1589]
30% Quota for women	-0.129	0.0986	0.0168	0.1215	0.1504
		[0.0985 , 0.0987]	[0.0167 , 0.0169]	[0.1215 , 0.1216]	[0.1503 , 0.1504]
50% Quota for women	-0.084	0.0829	0.0157	0.1043	0.1439
		[0.0828 , 0.0830]	[0.0156 , 0.0157]	[0.1042 , 0.1043]	[0.1438 , 0.1439]

Notes: This table presents the results from different counterfactual exercises that modify the admission process in Engineering either by increasing capacity or by prioritizing the admission of women using quotas (see Section 5 for details). Column (1) shows the gender gap under different counterfactual assignments. Columns (2) and (3) present the gender gap in returns and match effects obtained under different counterfactual assignments using the estimates from our main model. Column (4) shows the overall gender earnings gap resulting from each counterfactual assignment, and column (5) shows the overall gender earnings gap when adding a prediction for graduation.

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Online Appendix for:

Returns to Fields of Study and the Gender Earnings Gap

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February 2024

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A Data Appendix

In this section, we discuss additional details regarding the sample used in our analysis. As briefly alluded to in the appendix, our earnings are top-coded so we discuss our imputation procedure. We also provide more detail about our categorization of majors that are crucial in our analysis. Last, we report details of our AKM (Abowd et al., 1999) estimation procedure that is used in our analysis of the role of firm sorting.

A.1 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 ranges, and region controls.

Then, we impute an uncensored value for each censored observation using the estimated parameters of these models and random drawings ϵ 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 maximum (censoring limit), $X'\hat{\beta}$ is the tobit prediction, and $\hat{\sigma}$ is the standard deviation of the tobit error.

A.2 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: medicine, dentistry, pharmaceutical chemistry and biochemistry. Finally, we drop "*Agriculture*" and "*Services*" as they represent very few graduates (<5%) from non-homogeneous college programs in Chile.

A.3 AKM Estimation

Following the seminal study of the French labor market by Abowd et al. (1999), and more recent studies (Card et al., 2016, 2018, 2013), we estimate a so-called AKM model for log wages that includes additive effects for workers and firms. Specifically, our model for the log wage of person i in year t takes the form:

$$\ln w_{it} = \alpha_i + \psi_{J(i,t)} + \mathbf{X'}_{it}\beta + \varepsilon_{it}, \tag{8}$$

where α_i is a "person effect" capturing the (time-invariant) portable component of earnings ability, $\psi_{J(i,t)}$ is a function indicating the employer of worker i in year t, and ε_{it} is an unobserved time-varying error capturing shocks to human capital, person-specific job match effects, and other factors. The vector $\mathbf{X}_{it}$ includes year fixed effects and an third ordered polynomial of age interacted with five education categories (some primary education, some secondary education, complete secondary or incomplete higher education, complete higher education, and a "no data" category). Following Card et al. (2013), we recenter age around 40.

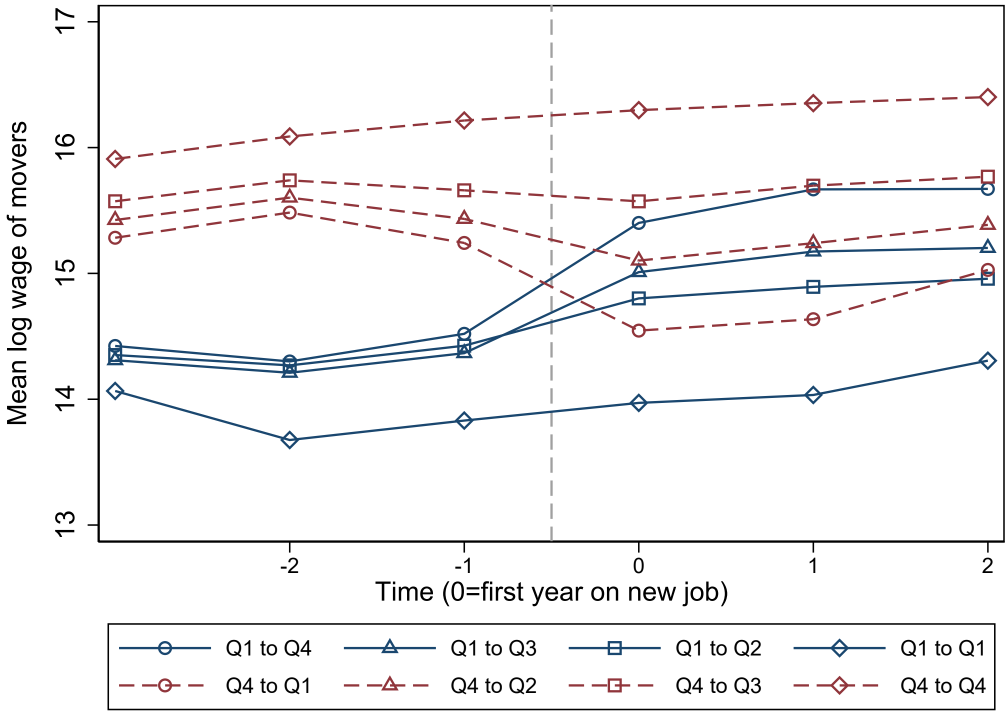
Importantly, the fixed effects in Equation (8) are identified by movers and can only be compared within connected sets. Thus, we estimate our model within the largest connected set of workers and firms, which includes 59,969,972 observations of 8,588,072 workers and 757,698 firms over an eleven years time window (2009-2019). Our estimates imply that 18% of the variance of wages is explained by firms. This is consistent with previous studies of wage determination with worker and firm fixed effects, which typically find that firm-specific premiums explain 20% of overall wage variation (Card et al., 2018).

For our analysis, we want to estimate firm-specific premiums $\psi_{J(i,t)}$ and a key assumption for identification of these parameters is "exogenous mobility", i.e., worker mobility must be uncorrelated with the time-varying residual components of wages. Following Card et al. (2013), we present a simple event-study analysis of the wage changes experienced by workers moving between different groups of firms. For this, we define firm quartiles based on the average pay of each firm. As explained in Card et al. (2018), if the AKM model is correct and firms offer proportional wage premiums for all their employees, then workers who move to higher-paying firms will on average experience pay raises, while those who move in the opposite direction will experience pay cuts. Moreover, the gains and losses for movers in opposite directions between any two groups of firms will be symmetric.[20]

Figure A.1 present our event study. Reassuringly, we find that the wage profiles exhibit steplike patterns: when workers move to higher-paying establishments, their wages rise and when they move to lower-paying establishments, their wages fall. The wage changes for people who stay in the same firm type are close to 0.

[20] This is in contrast to models of mobility linked to the worker-and-firm-specific match component of wages that imply that movers will tend to experience positive wage gains regardless of the direction of their move, violating the symmetry prediction.

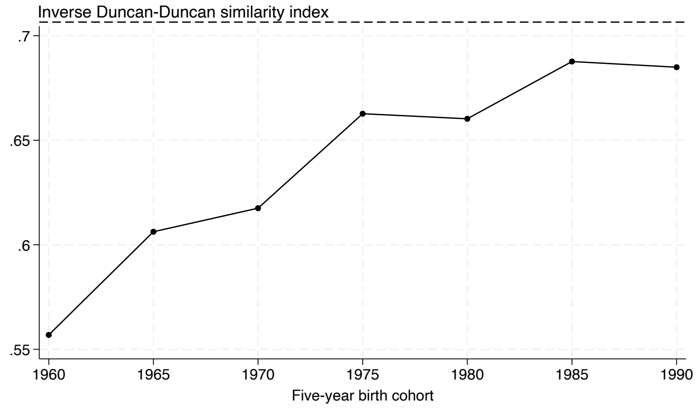
Figure A.1: Mean Wages of Job Changers



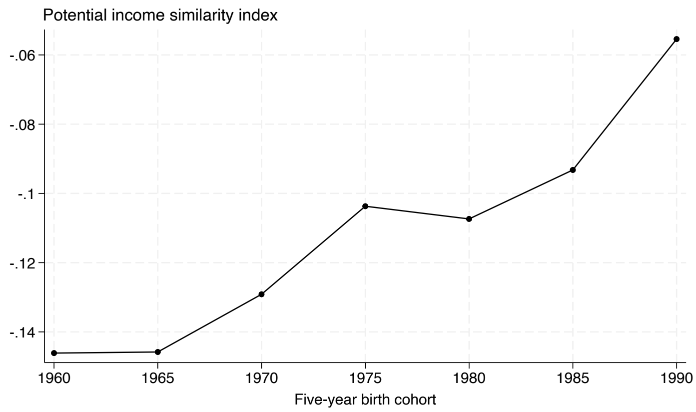
Note: In the spirit of Card et al. (2018), this figure shows the mean log wages of job changers classified by the quartile of the wages paid at origin and destination firms. We consider workers in the Unemployment Insurance dataset between 2009 and 2019 who are within the largest connected set.

B Additional Figures

Figure B.1: Similarity and Potential Wage Indexes by cohorts



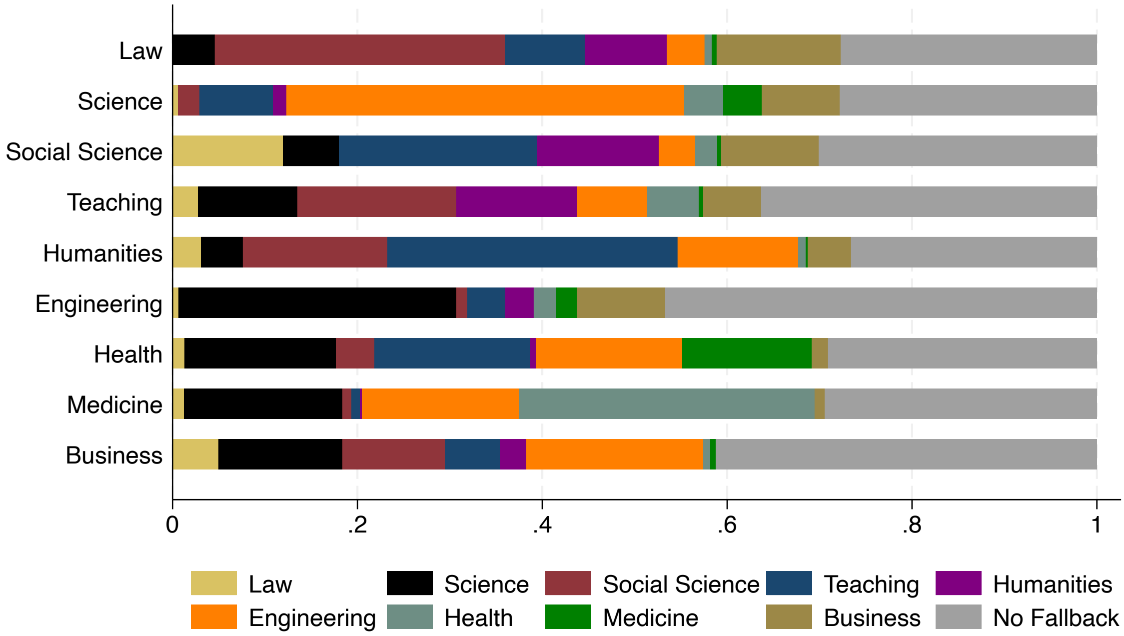
(a) Gender Similarity Index



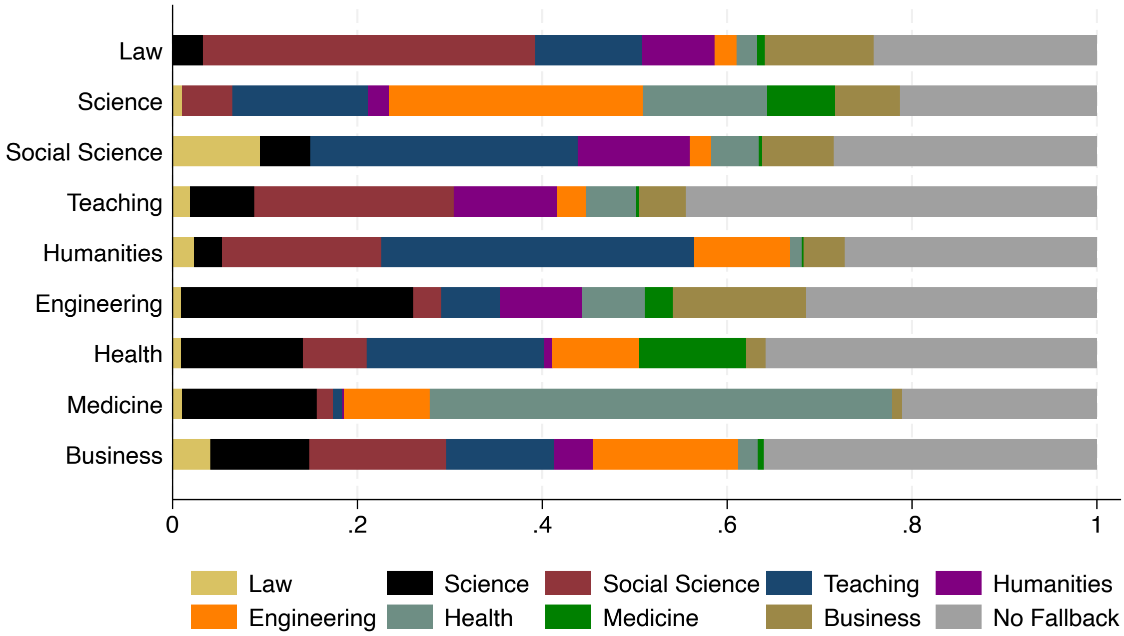
(b) Potential Wage Index

Note: 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 bachelorâs 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 B.2: Applicants' Fallbacks

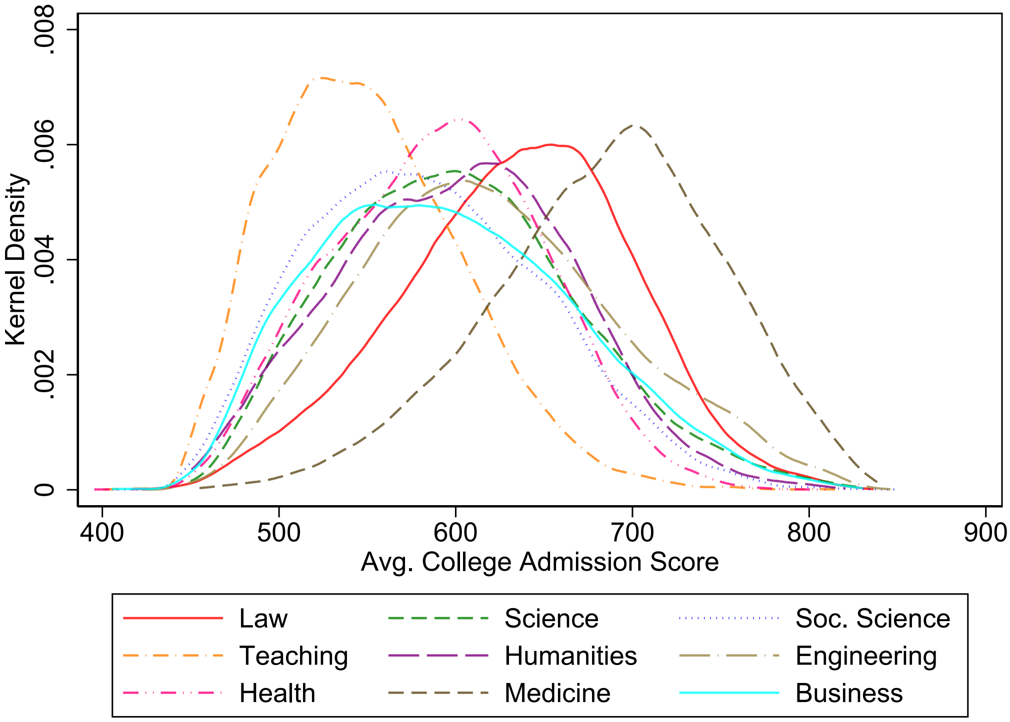


(a) Male



(b) Female

Notes: To construct this figure, we consider students' 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 through the centralized admission system between 2004 and 2007, graduated between 2007 and 2019, and were employed in 2019.



Notes: This figure shows the kernel densities of the college admission score (average between mathematics and language) of students graduating from different fields of study. We consider all students who applied through the centralized admission system between 2004 and 2007, graduated between 2007 and 2019, and were employed in 2019.

C Validating Empirical Results

Causal estimates of returns to field of study are central to our analysis. Estimating returns to field of study is challenging as it is fraught with many of the same difficulties that plague the estimation of returns to schooling (Altonji et al., 2012, Card, 2001).[21] In this section, we provide evidence that our estimates that account for preference heterogeneity produce estimates that are statistically similar to estimates that rely exclusively on quasi-random variation embedded in the assignment process (Abdulkadiroglu et al., 2017). This approach leverages both applicants' preferences and capacity constraints embedded in assignment to isolate quasi-experiments. A limitation of this approach, however, is that it is too demanding on the data, leading to small estimation samples and limitations in its ability to study rich selection patterns.

C.1 Quick Overview of Quasi-experiments Embedded in Centralized Assignment

Oversubscribed programs typically determine assignment using random or non-random tie-breakers, producing quasi-experiments that researchers can leverage. Abdulkadiroglu et al. (2017) demonstrate that centralized assignment embeds random assignment to programs that may not be oversubscribed, and thus, centralized matches provide an environment nesting multiple quasi-experiments above and beyond oversubscribed programs.

The core elements that create these stratified experiments are applicant types, which we denote by $\succ_i$ due to their dependence on preferences, tie-breakers r_i, and a vector of degree cutoffs τ. Therefore, based on the insights of Abdulkadiroğlu et al. (2022), our first approach relies on the fact that offers are (conditionally) mean independent of student ability:

$$E[u_{ij}|Z_i, R_i, \tau, r_i] = \sum_j \gamma_{ja} a_{ij} \ + \ \sum_j \gamma_{jp} p_{ij}(R_i, \tau, r_i) \ + \ g(R_i, \tau, X_i, r_i).$$

Conditional mean independence of field offers $Z_i = (Z_{1j}, \cdots, Z_{iJ})$ is implied by the stratified experiments embedded in centralized assignment, where $p_{ij}(R_i, \tau, r_i)$ is applicant i's assignment risk in field j, a_{ij} is an indicator if applicant i applies to field j, and $g(R_i, \tau, X_i, r_i)$ is a flexible polynomial that in turn depends on degree cutoffs, preferences, and applicants' tie-breaker. The necessity of $g(R_i, \tau, X_i, r_i)$ comes from the use of non-random tie-breakers in our setting so that p_{ij} is defined locally in an RDD-like framework. Settings that only rely on random tie-breakers do not need to adjust for running variables and are more akin to self-revelation analogs of Dale and Krueger (2002) and Mountjoy and Hickman (2021b).

Conditionally random offers to programs pave the way to estimates of α_j in a just-identified instrumental variables framework, instrumenting completion indicators D_{ij} with offer indicators Z_{ij}. In particular, we first predict major completion with the set offer indicators produced by centralized assignment:

$$D_i^j = \sum_k \pi_k Z_{ik} + \sum_k \gamma_{ka} a_{ik} \ + \ \sum_k \gamma_{kp} p_{ik}(R_i, \tau, r_i) \ + \ g(R_i, \tau, X_i, r_i) + e_i \quad j = 1, \cdots, J$$

This isolates random variation in major completion which we use to estimate returns in a 2SLS framework with corresponding reduced form equation:

$$Y_i = \sum_k \gamma_k Z_{ik} + \sum_k \gamma_{ka} a_{ik} \ + \ \sum_k \gamma_{kp} p_{ik}(R_i, \tau, r_i) \ + \ g(R_i, \tau, X_i, r_i) + u_i$$

This constant-effects framework isolates causal estimates of returns to field of study and is immune to the fallback-conditioning issues raised by Kirkeboen et al. (2016).

Finally, it is important to emphasize the key distinction between the two empirical approaches. While the first approach leverages all of the relevant information that produces stratified experiments within centralized assignment, the second approach abandons the reliance on capacity constraints. Doing so drops the reliance on local propensity scores and substantially increases the sample size. While the second approach provides additional structure to study potentially rich differences in sorting patterns with increased precision, it comes at the cost of

[21] The main problems are omitted variables that influence both choice and earnings. Insofar as students select themselves into particular fields on the basis of their anticipated future returns, OLS estimates of these returns would be biased as estimates of the causal impacts of field choice.

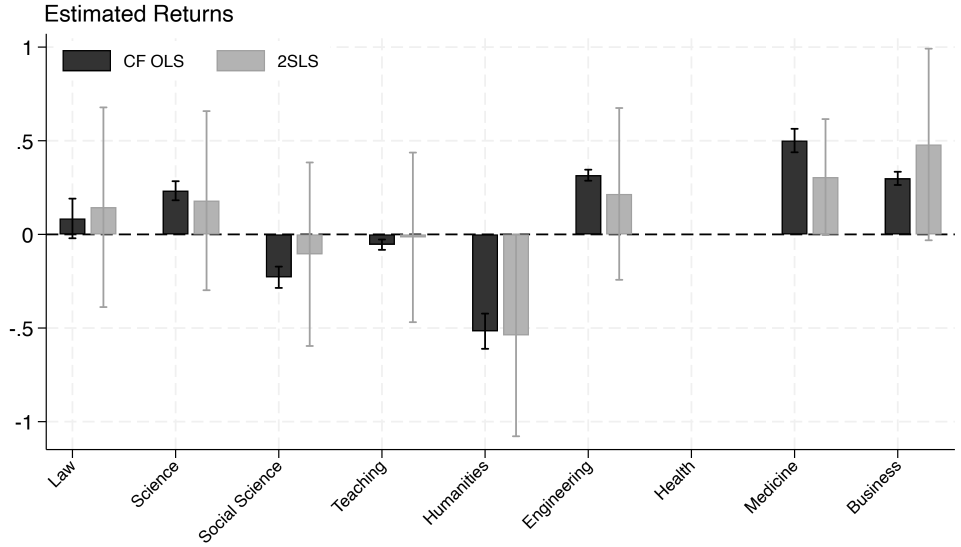
potentially introducing some bias. Nonetheless, the second approach is related to to the self-revelation principle of Dale and Krueger (2002) which has inspired recent important work (e.g., Abdulkadiroglu et al., 2020, Mountjoy and Hickman, 2021a). With these caveats in mind, a comparison of treatment effects estimated through both approaches is informative about the potential presence of selection bias not adequately captured by only adjusting for unobserved preference heterogeneity.

C.2 Evidence

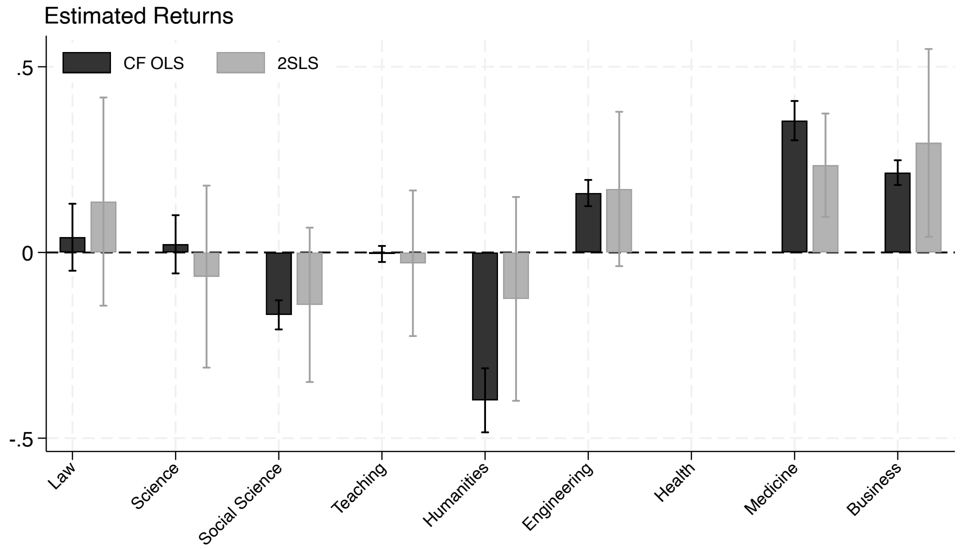
Appendix Figure C.1 reports comparisons of estimates between our preferred approach and the approach outlined above. We report estimates separately for men and women. Reassuringly, essentially all CF OLS point estimates are the same sign and confidence intervals of the instrumental variable approach include the CF OLS estimates. However, we also note across both panels in Figure C.1 a substantial loss of precision in the instrumental variable approach, with the standard errors commonly up to ten times as large as the control function approach and even more in some cases. We interpret the coincidence in the sign of estimates across both approaches as validation of the Control Function approach, while the gain in precision comes from leveraging the whole sample and additional structure embedded in the Control Function approach.

Overall, the results from both approaches tend to yield similar estimates providing reassuring evidence for the CF OLS approach which we exploit to explore rich sorting patterns and quantify their importance in relation to the gender earnings gap.

Figure C.1: Returns to Fields of Study: Alternative Methods



(a) Male



(b) Female

Note: This figure shows the returns to fields of study estimated using the two empirical approaches discussed in this section. 2SLS corresponds to instrumental variable estimates derived from models that adjust application indicators, assignment risk, and program-specific scores. CF OLS corresponds to estimates that only adjust for control functions derived from rank-ordered logit models. Panel (a) reports estimates for males, and Panel (b) reports estimates for females. We consider students who applied through the centralized admission system between 2004 and 2007, graduated between 2007 and 2019, and were employed in 2019. We also restrict the sample to students for whom we can recover estimates using both estimation methods (i.e., students with assignment risks for whom we can construct a control function to proxy for unobserved preferences).

D Additional Results

D.1 Earnings Results

D.2 Graduation

D.3 Fertility

E Counterfactual Details

E.1 Prediction Accuracy and Summary Statistics

This appendix describes the construction of the graduation predictions used in the counterfactual section. We predict graduation for students in the cohort of year 2007 up to YY years since High School graduation. We include as characteristics the income quintile of the student at the time when they applied to college, high school type dummies (public, private, and voucher), public health insurance dummy, years of schooling for mother and father, PSU scores (Math, Language, History, and Science), and each of the nine control functions from the choice model.

The prediction of graduation with a rich set of covariates is an ideal situation to leverage statistical learning techniques. Here we use Random Forest algorithm to generate predictions. See ESL for an introduction to the algorithm and Breiman (2001) for the original description.

In the counterfactual sample, we fit a Random Forest of 800 trees separately for each field of study. To do this, we first select students that were admitted to the field of study of interest. The graduation outcome includes graduation from any university (not only CRUCH). We use the out-of-bag vote share as the predicted graduation for a given student. For each tree, the algorithm selects a bootstrap subsample of the observations, so that about one-third of the observations are "out-of-bag" for a given tree. The out-of-bag vote share is constructed by running each observation through all of the trees for which it is out-of-bag, collecting the predictions (0 or 1 for a binary classification problem), and taking the average prediction for each observation.

Out-of-bag predicted graduation have significant explanatory power in this setting. Table E.1 presents descriptive exercises to show the performance of predicted graduation. Panel A shows the results of bivariate regressions between actual graduation from the field in the column with the out-of-bag predicted probability of graduation of the respective field. The results show unsurprisingly that the predicted graduation is a statistically significant association and with an R^2 between 0.03 and 0.17. Panel B presents the out-of-bag error rate which is around 0.32 and 0.42.

Table E.1: Predictive power of Random Forest out-of-bag graduation

	Law	Science	Social Science	Teaching	Humanities	Engineering	Health	Medicine	Business
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Bivariate regression of graduation on predicted graduation								
Predicted graduation	0.98	0.89	0.98	0.92	0.83	1.03	0.94	0.94	0.98
	(0.05)	(0.05)	(0.05)	(0.04)	(0.08)	(0.03)	(0.05)	(0.04)	(0.04)
N	2,481	5,741	4,553	9,782	2,848	12,095	4,613	2,097	5,517
R^2	0.15	0.06	0.08	0.04	0.03	0.12	0.07	0.17	0.10
	Panel B: Out-of-bag error rate								
Error Rate	0.36	0.40	0.37	0.42	0.42	0.36	0.40	0.32	0.37

Note: Each column of this table presents results of the predictive power of the predicted graduation for each field. Panel A presents results from a bi-variate regression between graduation from each field on out-of-bag predicted graduation from the random forest model. Panel B reports the error rate of the out-of-bag prediction. The

Table D.1: Gender Differences in Returns and Match Effects (Relative to non-graduation)

Dependent variable: Log Monthly Earnings in 2019

	Law (1)	Science (2)	Social Science (3)	Teaching (4)	Humanities (5)	Engineering (6)	Health (7)	Medicine (8)	Business (9)
					Panel A: Females				
Returns	0.384	0.374	0.203	0.353	-0.042	0.503	0.306	0.726	0.566
	(0.045)	(0.038)	(0.019)	(0.008)	(0.042)	(0.017)	(0.016)	(0.028)	(0.015)
Selection on Gains	0.049	-0.007	0.029	0.012	0.057	0.032	0.066	-0.006	0.020
	(0.015)	(0.022)	(0.010)	(0.006)	(0.017)	(0.012)	(0.008)	(0.012)	(0.008)
					Panel B: Males				
Returns	0.447	0.522	0.141	0.295	-0.161	0.628	0.301	0.832	0.615
	(0.053)	(0.024)	(0.029)	(0.013)	(0.047)	(0.013)	(0.025)	(0.032)	(0.016)
Selection on Gains	0.075	0.034	0.078	0.061	0.087	-0.001	0.077	0.006	0.049
	(0.018)	(0.012)	(0.014)	(0.008)	(0.019)	(0.009)	(0.014)	(0.014)	(0.008)
Est. Females = Est. Males									
Δ Returns (p-val)	0.365	0.001	0.066	0.000	0.059	0.000	0.859	0.012	0.019
Δ Match Effects (p-val)	0.254	0.104	0.005	0.000	0.234	0.032	0.509	0.517	0.006

Notes: This table presents the estimates obtained from our main regression model, presented in equation (3). The regression considers all applicants (not only college graduates) and leaves applicants who did not graduate as the omitted category (instead of health). The sample includes 164,810 observations of students who applied through the centralized admission system between 2004 and 2007 and for whom we observed labor market earnings in 2019.

Table D.2: Gender Differences in Returns and Match Effects: Private Sector Data

Dependent variable: Log Monthly Earnings in 2019 (Private Sector)	Law (1)	Science (2)	Social Science (3)	Teaching (4)	Humanities (5)	Engineering (6)	Medicine (7)	Business (8)
Panel A: Females								
Returns	0.079	0.118	-0.097	-0.052	-0.318	0.211	0.151	0.232
	(0.051)	(0.035)	(0.017)	(0.012)	(0.037)	(0.017)	(0.042)	(0.017)
Selection on Gains	0.045	-0.009	0.032	0.008	0.049	0.048	0.003	0.032
	(0.017)	(0.018)	(0.008)	(0.007)	(0.014)	(0.011)	(0.018)	(0.008)
Panel B: Males								
Returns	0.146	0.282	-0.155	-0.133	-0.396	0.357	0.180	0.332
	(0.059)	(0.023)	(0.027)	(0.017)	(0.042)	(0.015)	(0.049)	(0.018)
Selection on Gains	0.076	0.024	0.046	0.036	0.063	0.043	0.039	0.042
	(0.020)	(0.011)	(0.013)	(0.010)	(0.016)	(0.009)	(0.022)	(0.008)
Est. Females = Est. Males								
Δ Returns (p-val)	0.382	0.000	0.043	0.000	0.156	0.000	0.643	0.000
Δ Match Effects (p-val)	0.236	0.119	0.360	0.023	0.496	0.736	0.220	0.389

Notes: This table presents the estimates obtained from our main regression model, presented in equation (3), with health as the omitted field of study. In this case, we consider the earnings of workers in the private sector. The sample includes 80,937 observations of students who applied through the centralized admission system between 2004 and 2007, graduated between 2007 and 2019, and were employed in the private sector in 2019.

Table D.3: Gender Differences in Returns and Match Effects: Firm Premia

	Dependent variable: Firm Fixed Effects (Private Sector in 2019)							
	Law (1)	Science (2)	Social Science (3)	Teaching (4)	Humanities (5)	Engineering (6)	Medicine (7)	Business (8)
	Panel A: Female							
Returns	-0.184	0.153	-0.040	-0.008	-0.126	0.072	0.017	0.103
	(0.086)	(0.044)	(0.022)	(0.015)	(0.044)	(0.024)	(0.018)	(0.020)
Selection on Gains	0.059	-0.005	0.008	0.012	0.028	0.005	-0.009	0.021
	(0.029)	(0.022)	(0.011)	(0.009)	(0.017)	(0.016)	(0.009)	(0.010)
	Panel B: Male							
Returns	-0.125	0.050	-0.054	-0.056	-0.202	0.148	0.011	0.115
	(0.082)	(0.030)	(0.025)	(0.027)	(0.064)	(0.020)	(0.023)	(0.021)
Selection on Gains	0.057	0.036	-0.001	0.004	0.049	-0.008	-0.005	0.017
	(0.024)	(0.015)	(0.014)	(0.017)	(0.024)	(0.013)	(0.012)	(0.011)
Est. Females = Est. Males								
Δ Returns (p-val)	0.620	0.049	0.618	0.069	0.316	0.006	0.847	0.634
Δ Match Effects (p-val)	0.957	0.126	0.603	0.673	0.475	0.527	0.807	0.768

Notes: This table presents the estimates obtained from our main regression model, presented in equation (3), with health as the omitted field of study. In this case, we consider the firm premia estimated from an AKM model (Abowd et al., 1999, Card et al., 2013) as the dependent variable. The sample includes 79,949 observations of students who applied through the centralized admission system between 2004 and 2007, graduated between 2007 and 2019, and were employed in the private sector in 2019.

Table D.4: Gender Differences in Returns and Match Effects: Total Earnings

Dependent variable: Total Earnings in 2019

	Law	Science	Social Science	Teaching	Humanities	Engineering	Medicine	Business
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Females				
Returns	-38.345	-176.306	-366.829	-32.720	-781.747	168.539	722.897	397.598
	(62.304)	(62.859)	(24.430)	(14.940)	(40.728)	(33.420)	(59.106)	(30.701)
Selection on Gains	62.980	-23.476	24.738	-31.797	69.011	91.788	48.114	59.588
	(21.619)	(32.852)	(12.668)	(9.314)	(15.295)	(22.991)	(26.684)	(16.045)
				Panel A: Males				
Returns	-155.634	343.330	-434.204	-101.929	-889.884	614.404	1143.086	607.921
	(71.254)	(51.113)	(32.440)	(19.226)	(40.682)	(31.271)	(71.950)	(37.186)
Selection on Gains	147.986	6.250	71.761	11.078	147.397	70.864	15.031	67.510
	(26.248)	(25.528)	(19.129)	(13.897)	(16.480)	(21.082)	(33.691)	(19.979)
Est. Females = Est. Males								
Δ Returns (p-val)	0.207	0.000	0.068	0.000	0.048	0.000	0.000	0.000
Δ Match Effects (p-val)	0.012	0.475	0.040	0.010	0.000	0.502	0.441	0.757

Notes: This table presents the estimates obtained from our main regression model, presented in equation (3). In this case, we consider the sum of earnings instead of the log of earnings to account for the extensive margin. The sample includes 142,651 observations of students who applied through the centralized admission system between 2004 and 2007, graduated between 2007 and 2019, and were employed in 2019.

Table D.5: Gender Differences in Graduation Upon Acceptance

Dependent variable: Ever Graduation

	Law (1)	Science (2)	Social Science (3)	Teaching (4)	Humanities (5)	Engineering (6)	Health (7)	Medicine (8)	Business (9)
Panel A: Females									
Returns	-0.038	0.152	0.159	0.252	0.052	0.177	0.259	0.310	0.181
	(0.055)	(0.017)	(0.017)	(0.008)	(0.029)	(0.012)	(0.012)	(0.028)	(0.020)
Selection on Gains	0.048	0.009	0.021	-0.015	0.025	0.046	0.000	-0.021	0.016
	(0.018)	(0.009)	(0.008)	(0.005)	(0.011)	(0.009)	(0.006)	(0.011)	(0.008)
Panel B: Males									
Returns	-0.036	0.101	0.026	0.144	-0.041	0.108	0.179	0.263	0.109
	(0.054)	(0.016)	(0.023)	(0.014)	(0.036)	(0.010)	(0.019)	(0.033)	(0.023)
Selection on Gains	0.040	-0.005	0.046	-0.004	0.041	0.035	0.005	-0.017	0.017
	(0.017)	(0.008)	(0.011)	(0.008)	(0.013)	(0.007)	(0.010)	(0.014)	(0.009)
Est. Females = Est. Males									
Δ Returns (p-val)	0.979	0.025	0.000	0.000	0.042	0.000	0.000	0.270	0.015
Δ Match Effects (p-val)	0.736	0.273	0.066	0.226	0.376	0.331	0.656	0.837	0.963

Notes: This table presents the estimates obtained from a variation of our main regression model, presented in equation (3). In this case, the dependent variable is ever-graduation, and the independent variables are indicators of acceptance into (instead of graduation from) fields of study. We only consider acceptance at CRUCH institutions since only for those can we observe applicant scores and program admission cutoffs. We consider all college applicants (not only college graduates) and leave those who did not graduate as the omitted category. The sample includes 172,323 observations of students who applied through the centralized admission system between 2004 and 2007.

Table D.6: Fertility: Children 12 years after college application

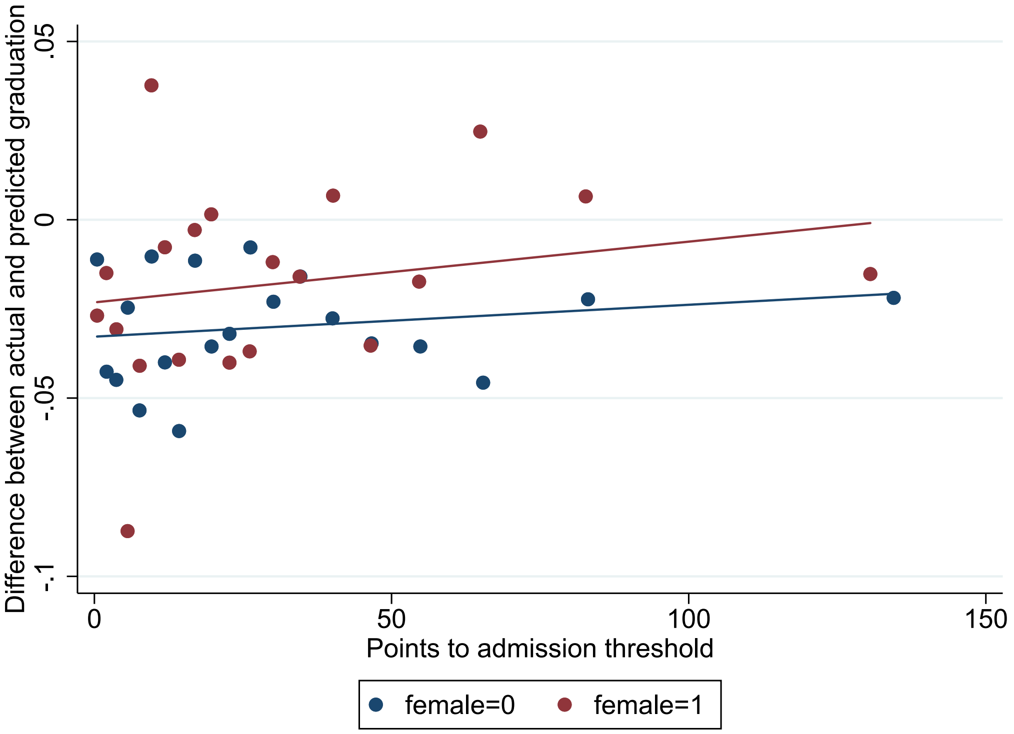
Dependent variable: Any Child 12 Years After College Application

	Law	Science	Social Science	Teaching	Humanities	Engineering	Medicine	Business
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Females				
Returns	-0.118	-0.083	-0.024	0.095	-0.103	-0.043	-0.095	-0.001
	(0.017)	(0.018)	(0.010)	(0.007)	(0.015)	(0.010)	(0.013)	(0.009)
Match Effects	0.009	-0.003	-0.001	-0.005	0.024	-0.007	-0.001	0.008
	(0.006)	(0.009)	(0.005)	(0.004)	(0.006)	(0.007)	(0.006)	(0.005)
				Panel B: Males				
Returns	-0.126	-0.115	-0.118	- 0.026	-0.201	-0.076	-0.090	-0.079
	(0.018)	(0.012)	(0.012)	(0.009)	(0.015)	(0.008)	(0.013)	(0.009)
Match Effects	-0.002	0.002	0.004	-0.007	0.017	0.007	0.012	-0.005
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)
Est. Females = Est. Males								
Δ Returns (p-val)	0.743	0.119	0.000	0.000	0.000	0.003	0.781	0.000
Δ Match Effects (p-val)	0.229	0.689	0.521	0.717	0.384	0.086	0.138	0.050

Notes: This table presents the estimates obtained from our main regression model, presented in equation (3), with health as the omitted field of study. The sample includes 140,690 observations of students who applied through the centralized admission system between 2004 and 2007, graduated between 2007 and 2019. The mean of the dependent variable among Health graduates is 0.391.

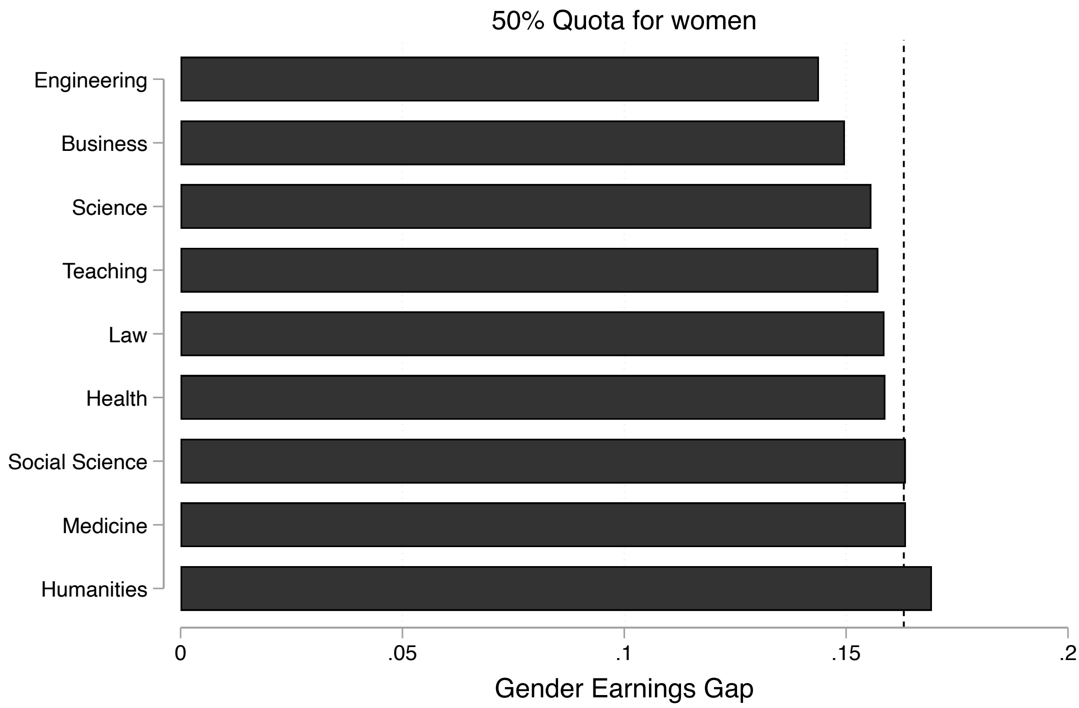
E.2 Additional Results

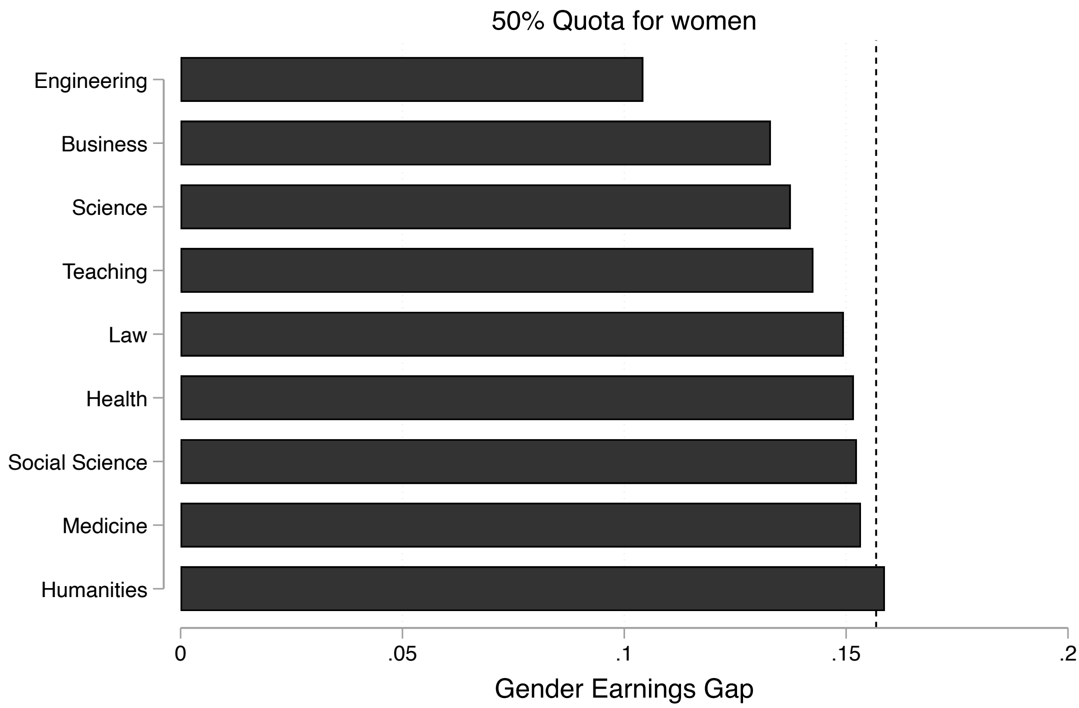
Figure E.1: Prediction error around the admission cutoff by gender



Notes: This figure shows the relationship between prediction error from the Random Forest prediction of graduation and the distance to admission cutoff among students admitted to Engineering programs. The figure shows that the error rate is mostly flat just above the cutoff which suggests that there is no systematic improvement in our models' ability to predict graduation at different test scores.

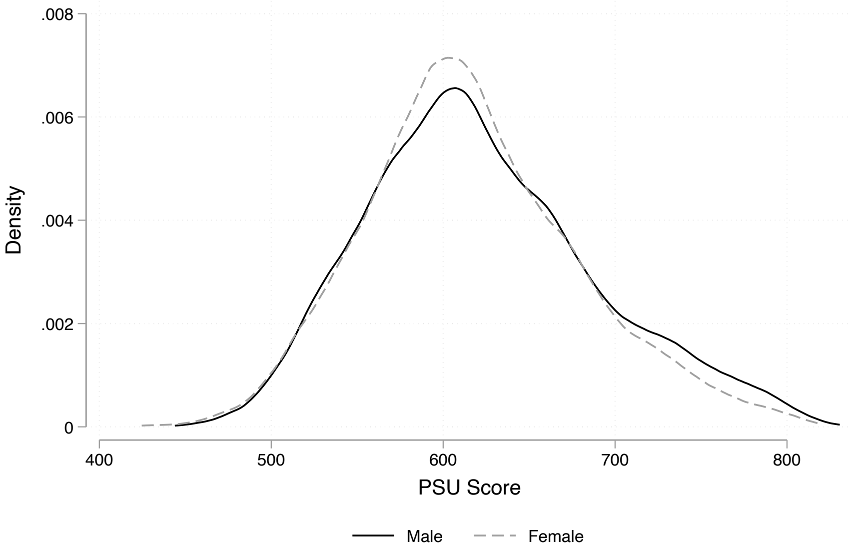
Figure E.2: Counterfactual Assignment Policies



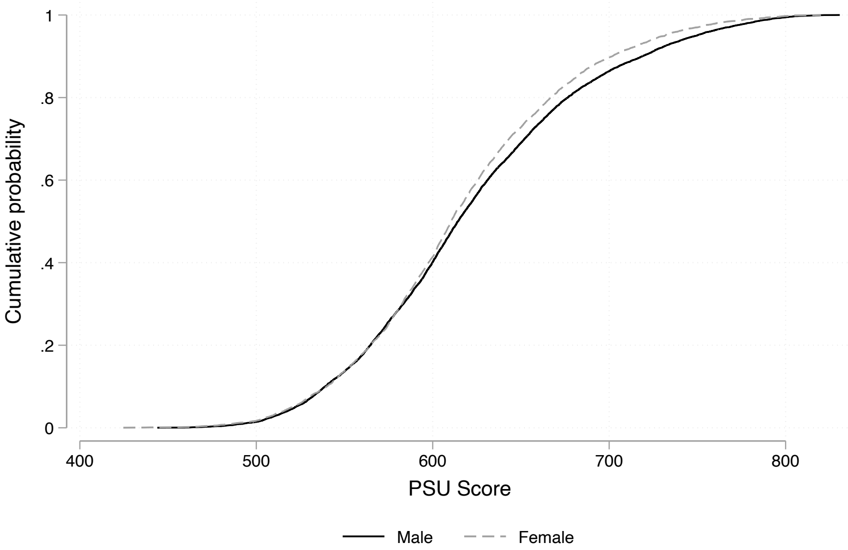


Notes: These figures show the gender earnings gap under different counterfactual assignment policies. In panel (a), each bar shows the overall gender earnings gap under a policy that increases seats by 50% in a given field of study. In panel (b), each bar shows the overall gender earnings gap under a policy that creates a 50% quota for women, given seats, in each field of study. The black vertical line shows the baseline gender earnings gap among college graduates in Chile.

Figure E.3: PSU Distribution Among Engineering Applicants



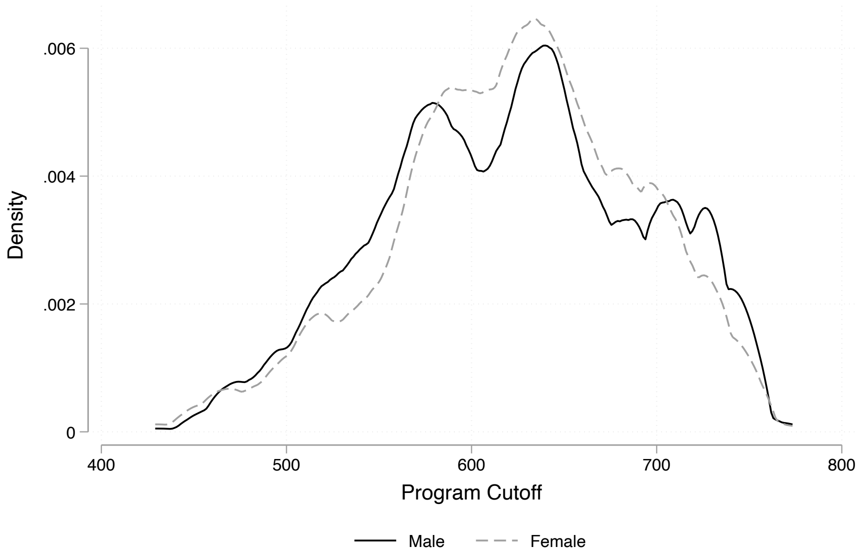
(a) Density



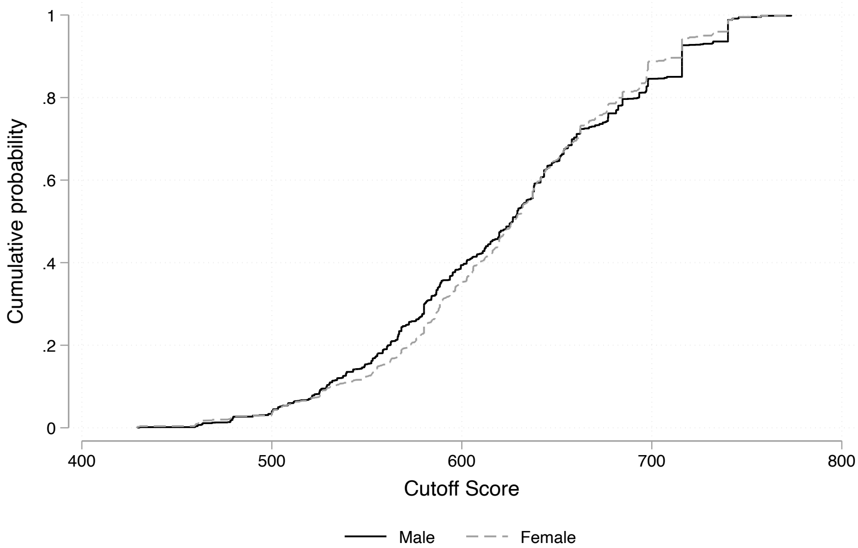
(b) CDF

Notes: This figure reports density and cumulative distribution plots of PSU scores among applicants who rank Engineering at the top of their rank-ordered list. Panel (a) reports the density and Panel (b) reports the CDF. Figures restrict to applicants with PSU scores above the minimum required to apply to the CRUCH system during 2004-2007.

Figure E.4: Top-Ranked Program Cutoffs



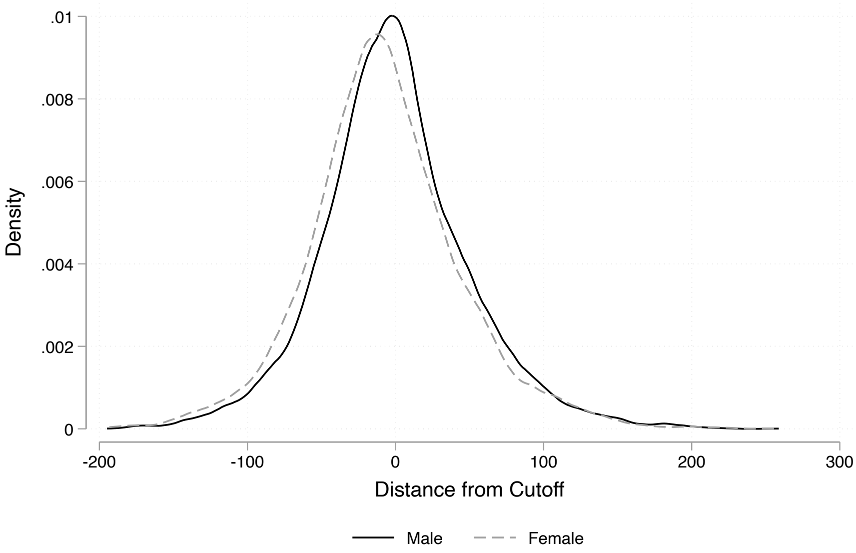
(a) Density



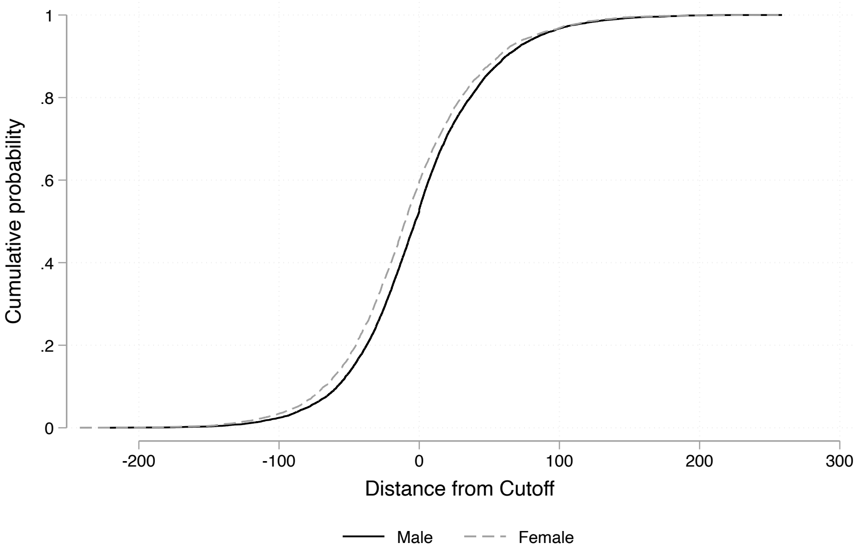
(b) CDF

Notes: This figure reports density and cumulative distribution plots of program cutoffs among applicants who rank Engineering at the top of their rank-ordered list. Panel (a) reports the density and Panel (b) reports the CDF. Figures restrict to applicants with PSU scores above the minimum required to apply to the CRUCH system during 2004-2007.

Figure E.5: Distance from Cutoff to Top-Ranked Program



(a) Density



(b) CDF

Notes: This figure reports density and cumulative distribution plots of the distance to program cutoff among applicants who rank Engineering at the top of their rank-ordered list. Panel (a) reports the density and Panel (b) reports the CDF. Figures restrict to applicants with PSU scores above the minimum required to apply to the CRUCH system during 2004-2007.