The Only Women in the Room: When College Peers Matter the Most

Josefa Aguirre;[*] Juan Matta; [†] Ana María Montoya [‡]

February 22, 2021

Abstract. This paper studies the long-term effects of college peers. To address peer endogeneity we exploit variation in peer characteristics within programs and across cohorts. Combining administrative educational records with data on labor earnings, marriage, and fertility, we find that high-ability female peers (as measured by math college admission test scores) positively impact women's graduation rates, earnings, and marriage market outcomes, while decreasing fertility rates. Conversely, high-ability male peers exert a stronger and contrasting influence. They significantly decrease women's graduation rates and earnings while increasing fertility rates. Our results are driven by women pursuing STEM fields, who are significantly disadvantaged by having high-ability male peers. In contrast, we find no impact of peer ability on men's outcomes in STEM or non-STEM fields.
Keywords: Peer Effects, College, Gender, Chile

1 Introduction

Two decades have elapsed since the works of Sacerdote (2001) and Zimmerman (2003) initiated a productive literature that has carefully investigated peer effects in higher education. While the specific findings in this literature differ, there is a clear indication that at least some peers are in fact relevant for academic performance; and that peers can be especially influential for social outcomes (e.g., crime, drinking behavior) and career choices. However, we still have a long way to go in understanding how peer influence interacts with gender. Social interactions are not only stronger among same-sex peers due to homophily, but can be very different among women than among men. Moreover, cross-sex interactions could affect men and women differently.

Recently, the issue of how peer effects interact with gender has attracted particular attention in the literature exploring gender differences in education and the labor market. The lack of female peers has been identified as one of the many barriers that women face when attempting to enter fields where they are underrepresented. In such contexts, female peers could be particularly valuable to women, not only as a source of networks, information, and support, but also because they can provide gender-specific advice on navigating a male-dominated and often hostile environment (Hampole et al., 2021; Bostwick and Weinberg, 2022). Male peers could also be beneficial, to the extent that they encourage women to pursue more lucrative career paths or provide access to larger networks (Thomas, 2021). However, some authors suggest that a higher share of male peers, particularly high-ability male peers, could deter women from highly competitive and male-dominated fields, such as STEM (Calkins et al., 2020; Fischer, 2017).

In this paper, we study the effects of quasi-random variation in the quality of male and female college peers (as measured by their math college admission test scores) on long-term outcomes of men and women, including graduation, earnings, fertility and marriage. To see how our results vary across fields, we divide our sample between students attending STEM and non-STEM programs.

Our findings are consistent with prior research indicating that college peers have a significant impact on women's academic choices, while men's choices are less affected (Fischer, 2017; Lim and Meer, 2020). Specifically, we find that the quality of peers is particularly important for women in STEM. Enhancing the quality of female peers by one standard deviation increases their likelihood of graduating from any university program by 0.8 percentage points. However, increasing the quality of male peers has the opposite effect, decreasing their likelihood of graduating from their chosen STEM program by 1.1 percentage points. In contrast, we do not find conclusive evidence that peer quality has a significant impact on the graduation outcomes of women in non-STEM fields or men in either STEM or non-STEM fields.

The quality of peers also affects labor market outcomes for women. Having better male peers decreases earnings for women 10 years after graduating from high school, while having better female peers can increase earnings (although this last result is non-significant). These findings apply to women in all fields, but are particularly pronounced for those in STEM. Our analysis, although somewhat noisy, suggests that the decrease in earnings associated with better male peers may be due to a decrease in women's employment rates and accumulated work experience, as well as lower wages for women who are employed. Conversely, the increase in earnings associated with better female peers appears to be linked to higher employment rates and more work experience among women.

The findings regarding labor market outcomes align with the notion that women, particularly those in STEM fields, may not experience significant benefits from having access to a better network of male peers. Our data support this idea by indicating that women tend to be more concentrated across firms compared to men. This concentration is particularly prominent among women in STEM, who are more likely to work at the same firm as a same-sex peer when compared to men in STEM or women in non-STEM fields. This observation supports the hypothesis of gender-segregated networks in STEM.

Furthermore, our analysis reveals no evidence suggesting that women's labor market outcomes improve with the presence of high-performing male peers. Not only do earnings decrease in response to having better-performing male peers, but access to these peers does not enhance the probability of working at a firm affiliated with other program alumni, male program alumni, or high-performing male program alumni.

In terms of fertility, our findings indicate that having better female peers in STEM programs is associated with a decrease in the number of children women have had by the age of 28. Conversely, having better male peers in STEM programs is linked to an increase in the number of children women have had. This suggests that women in STEM who are exposed to higher-performing female peers may place a greater emphasis on career development, potentially leading to a delay in starting a family. On the other hand, the presence of accomplished male peers may have a contrasting effect, possibly encouraging women to consider starting a family earlier.

Regarding marriage market outcomes, our results, albeit with some noise in the estimates, indicate a positive impact of having better female peers on the characteristics of women's partners. However, we do not observe a similar effect in relation to the presence of better male peers. These results challenge the common belief that accessing a more accomplished network of peers of the opposite sex would enhance marriage market outcomes, while having access to a more accomplished network of peers of the same sex would hinder such outcomes. Instead, our findings suggest that in this particular context, the potential benefits women derive from having better female peers, in terms of educational and career achievements, may exert a stronger influence on marriage market outcomes than any potential negative impact resulting from increased competition within this pool of high-performing female peers. On the other hand, the potential harm women may experience from having better male peers, in terms of educational and career achievements, may have a more pronounced influence on marriage market outcomes than the potential advantages of having access to a better pool of male peers.

The setting we study offers three unique advantages for investigating peer effects in higher education. First, as in many other countries, but unlike the U.S., postsecondary students in Chile enroll directly into a specific major in a particular college institution. Students entering the same college-major combination (or program for short) in the same year constitute a well-defined group of peers (a class) that is likely to be relevant from academic and professional perspectives. This stands in contrast to many studies of college peer effects that rely on random assignment of roommates or college peers who have not yet chosen a major, and who may follow very different career paths.[1]

[1]The use of random assignment of roommates as a strategy was inaugurated by Sacerdote (2001) and Zimmerman (2003), but many others have followed them, e.g., Stinebrickner and Stinebrickner (2006)); Foster (2006); Lyle (2007); Kremer and Levy (2008); Han and Li (2009); Hayashi (2016); and Zhang and Pu (2017). Although roommates spend

A second advantage of the setting is that it allows us to study peer effects in higher education using a nationwide database covering 25 college institutions and over 100 majors in every area of study. To the best of our knowledge, this is the first paper to study peer effects across several higher education institutions. Notably, these institutions serve students from different socioeconomic backgrounds and different levels of academic ability, reducing concerns with external validity raised in the case of studies that focus on highly selective colleges or military academies.

Finally, a third advantage of this setting is that it gives us access to comprehensive information regarding students' characteristics and test score performance at baseline. This rich dataset allows us to explore how various peer characteristics, beyond gender alone, can influence long-term outcomes. Furthermore, we can leverage the linkage between students and a wide array of administrative records on education, labor market activities, fertility, and marriage. This enables us to examine long-term effects that extend far beyond educational attainment, all without the need to rely on survey-based data.

One of the major challenges in the identification of peer effects is the fact that individuals are rarely assigned to peer groups at random. To the extent that similar students are likely to enroll in the same program, we might mistakenly attribute to peer influence what is really the result of peers being similar, or "correlated effects" to use Manski's (1993) terms. In the setting we study, student selection has two parts: students choose which programs they apply to and programs can select their students from the pool of applicants. We deal with students' self-selection into programs by exploiting variation in peer characteristics across cohorts and within programs. This strategy is very common in the literature studying peer effects in primary and secondary education.[2] To deal with the programs' selection of students, on the other hand, we take advantage of Chile's unique system of admission to higher education. The system is such that whenever a program is oversubscribed, seats are assigned exclusively based on applicants' scores on an SAT-like standardized admission test. Since this is a case of selection on observables, we deal with it by controlling for students' test scores.

We conduct several robustness checks to support our identification assumption. Firstly, we show that changes in peer composition do not correlate with changes in predetermined individual characteristics. Secondly, we explore the weights assigned to different groups/periods in our peer effects estimates. Following the recent literature on two-way fixed effects, we asses whether these weights strongly correlated with factors that could potentially indicate stronger treatment

---

significant time together and often become friends, the fact that many of these studies have failed to identify robust peer effects on academic achievement has called into question whether roommates constitute peers of "potential influence" (Stinebrickner and Stinebrickner, 2006). A few studies have examined peer effects in military academies using random assignment of students to companies or squadrons, where peers interact in class as well as in residences (Lyle, 2007 Carrell et al., 2009). Although this increases the potential for academic interaction with peers, it does so in a very specific context which may or may not generalize to other higher education settings.

[2] See for instance Hoxby (2000b), Angrist and Lang (2004), Gould et al. (2009), Lavy and Schlosser (2011), Lavy et al. (2012), Black et al. (2013), Bifulco et al. (2014), Merlino et al. (2019), Cools et al. (2019) and Olivetti et al. (2020).

effects. By doing so, we address the concern of potential bias in our results (De Chaisemartin and d'Haultfoeuille, 2020). Lastly, we leverage Chile's centralized college admission system to implement an alternative strategy. In this approach, we control for students' characteristics (such as preferences and test scores) and exploit variation in peer quality that arises solely from changes in program capacities or ranking criteria. These factors are driven by institutional choices and are unlikely to be directly related to students' future outcomes.

Our paper contributes to several strands of literature. Results are closely related to a growing literature looking at how the gender composition of peers in high school or college affect women's performance or major choices. Most of these papers exploit variations in high school peers, finding mixed results (Hill, 2015; Brenøe and Zölitz, 2020; Goulas et al., 2018; Schneeweis and Zweimüller, 2012; Anelli and Peri, 2019; Mouganie and Wang, 2020).[3] Papers looking at college peers include Calkins et al. (2020) who exploits the adoption of coeducation by US colleges, and finds that the influx of men deterred women from STEM majors, and Fischer (2017) who exploits variation in peers ability at a first year STEM course in college and finds that having higher ability peers decreases women's probability of graduating from a STEM degree.

Our study contributes to this literature by looking instead at the effect that college peers have on students who have already chosen a specific major. This allows us not only to look at a population that has already made a major choice, but also to look at a peer group that is more comprehensive, salient and meaningful to these students, particularly for long-term outcomes. Our rich dataset also allows us to look at several peer characteristics including peer academic achievement and socioeconomic status. We are able to show that in our setting academic ability of male and female peers matters the most.

Studies that look at peer effects in context where students are already enrolled in a specific field include Zölitz and Feld (2021) and Feld and Zölitz (2022) who exploit variation in peer characteristics in the context of a Dutsch business school; Hampole et al. (2021) and Thomas (2021) who look at the impact of gender composition on labour outcomes of women in the context of MBA programs; and Bostwick and Weinberg (2022) who looks at the impact of gender composition on

[3] Brenøe and Zölitz (2020), for instance, use data from Denmark and find that having a larger proportion of female peers in high school reduces women's probability of enrolling in and graduating from STEM programs, reduced their earnings, and increases their fertility. Other papers, however, indicate that a higher share of female peers in high school can be beneficial for women. Goulas et al. (2018), for instance, use data from Greece and find that a higher share of females in a school or neighborhood improves both genders' subsequent performance, university matriculation rates, and in the case of women, their probability of pursuing STEM degrees. Similarly, Schneeweis and Zweimüller (2012) show that girls with more female peers are less likely to choose female-dominated school types and more likely to choose a male dominated school type in Austria. Mouganie and Wang (2020) uses data from China and look at the impact of peer performance rather than female share, and find that exposure to high-performing female peers in mathematics increases the likelihood that women choose a science track during high school, while exposure to more high-performing males decrease this likelihood. Consistent with the idea that male peer may be detrimental for women, Hill (2015) finds that a student's share of opposite gender school friends negatively affects high school GPA. On the contrary, Anelli and Peri (2019) use data from Italy and find no effect of the gender composition of peers in high school on college major choices and labour market outcomes.

degree completion for women pursuing PhD programs in STEM . Findings suggest that a higher share of female peers could shift women towards more female-dominated majors within business and lead to lower earnings for them (Thomas, 2021; Zölitz and Feld, 2021; Feld and Zölitz, 2022). At the same time, for some women, having more female peers could help them presumably navigate these male-dominated environments and succeed in obtaining their PhD or reaching a managerial position (Bostwick and Weinberg, 2022; Hampole et al., 2021). We contribute to this literature by providing new evidence coming from administrative records for students in 25 institutions and over 100 majors, which allows us to better understand in which situations and for whom peers matter the most. Importantly, while previous studies rely mostly on survey data to look at the long-term effects of college peers, we are able to access administrative records to look at earnings, fertility and marriage. Our results show that peer effects are particularly relevant for women pursuing male-dominated fields, such as STEM. Instead, while women may benefit from having better female peers in non-STEM fields, results are smaller in magnitude, and we find no evidence that they may be harmed by the presence of better male peers outside of STEM.

Our results further contribute to the literature that uses laboratory and field experiments to analyze how women's behavior changes in response to the presence of male peers, particularly in highly competitive environments such as STEM programs. Several papers have shown women's willingness to compete and aptitude in competition are lower in mixed-gender relative to single-sex environments (Gneezy et al., 2009; Niederle and Vesterlund, 2007, 2008; Kamas and Preston, 2012). These differences appear to depend on prevailing social norms (Gneezy et al., 2009), exposure to male peers in elementary school (Booth and Nolen, 2012a,b), and whether actions will be observed by male peers (Bursztyn et al., 2017). This paper contributes by providing evidence of the implications that this may have for women in a real-world setting. In line with previous papers, we find that women are hurt by the presence of high-ability male peers, but men are not; which is consistent with high-achieving male peers creating a classroom atmosphere that men appreciate and women do not.

2 Theoretical Effects of Peer Quality

Before turning to estimation, it is useful to outline potential ways in which higher-achieving peers may impact an individual's post-college outcomes. In this section, we discuss two potential channels: human capital accumulation and social networks. We discuss these channels in detail and highlight some of the gender-based differences that may arise.

The first channel through which higher-performing peers can affect individuals' long-term outcomes is their human capital accumulation and likelihood of graduation. However, the effects of high-achieving peers are complex and could differ by gender. On the one hand, having high-achieving peers can be beneficial as it may lead to knowledge spillovers during class or study sessions, motivate students to work harder to keep up with their high-performing peers, or establish higher norms and expectations for academic and career achievement. On the other hand, a classroom full of high achievers may negatively impact self-perception and reduce effort incentives as it becomes harder to be ranked highly.

Moreover, male and female peers may affect male and female students differently. Students may benefit more from the presence of high-achieving same-sex peers due to homophily or the influence of role models. Additionally, men and women may react differently to increased competition, given differences in psychological attributes and risk preferences. Research has shown that women tend to be more risk-averse and underperform in competitive environments, displaying a lower degree of self-confidence about their own abilities (Niederle and Vesterlund, 2007; Gneezy et al., 2009). Moreover, papers have shown that women tend to be more responsive to their grades (Rask and Tiefenthaler, 2008; Ost, 2010). This heightened sensitivity to academic performance could significantly impact their college choices, potentially deterring them from pursuing fields such as STEM, which are often associated with lower grades (Ahn et al., 2019)

The impact of peers on human capital accumulation could have significant effects on labor market and marriage market outcomes. An increase (or decrease) in human capital accumulation should lead to higher (or lower) productivity and wage offers. These, in turn, could affect marriage market outcomes. For men, educational and labor market outcomes are often thought to improve marriage prospects, but the effect is less clear for women. While higher education could increase women's household production and labor market outcomes, making them more attractive, women who prioritize their careers may be less willing to focus on domestic production within marriage and to forgo their own career progression to support their partner's advancement. Additionally, men and women may conform to traditional gender norms within their relationships, where the dominant earner is male (Bertrand et al., 2015). High career ambition may be perceived as an undesirable trait in a potential wife (Bursztyn et al., 2017). In fact, preference estimates from an online dating platform indicate that while men and women both value income positively, women place twice as much weight on it than men do (Hitsch et al., 2010).

In addition to shifting the distribution of wage and marriage offers, education can also impact the criteria that individuals consider when accepting or rejecting such offers. For instance, a woman who expects to receive high-wage offers may prioritize her independence and set a higher standard for accepting a marriage offer. In contrast, a woman who gains access to additional financial support through marriage may set a higher wage threshold before accepting a job offer.

A second channel through which higher-achieving peers can impact individuals is through social networks. Having higher-performing peers can provide lower access costs to an improved professional network and marriage pool. The effects of this on labor market outcomes are uncertain, as access to a better network of peers, particularly same-sex peers, could improve professional offers, but it could also mean that the set of closest competitors in the professional market are of higher caliber, making it more challenging to stand out. Similarly, the effects on marriage market outcomes will depend on whether we are looking at same or different-sex peers. Access to a better network of different-sex peers could improve marriage market offers, while access to better same-sex peers could increase competition and decrease marriage market outcomes.

3 Institutional Setting

The Chilean postsecondary education sector consists of 60 universities that offer college degrees and 122 institutions that offer technical degrees. College degrees typically take 5 years to complete. Of the total number of universities, 25 participate in a centralized admission system called SUA (for *Sistema Único de Admisión*, or Unified System of Admission).[4] Universities that do not participate in this admission system are predominantly private and typically serve lower-scoring students. The 25 universities that participate in SUA are all non-profit, but can be public, private, or private-parochial. These universities span a wide range of selectivity levels.

In this study we focus on students enrolling in one of these 25 institutions. In order to apply to these institutions, students must take an SAT-like standardized test called PSU (for *Prueba de Selección Universitaria* or University Selection Test.) There is only one chance to take the test each year. The PSU consists of exams in mathematics and language, and students have the option to take additional tests in subjects such as science and history. Prior to 2004, students had to choose among six subject tests, but as of 2004, they must choose between science and history. Test scores and high school GPA are scaled to a distribution ranging from 150 to 850, with a mean and median of 500.

After taking the PSU and being informed of their test scores, students submit their applications to the system using an online platform. As in many other postsecondary education systems, students in Chile apply directly to specific majors within postsecondary institutions (we refer to the combination of a major and a college as a *program*). Each year, institutions must define ex-ante the weights each program will assign to the different sections of the PSU as well as to high school GPA when ranking candidates. Because weights can vary across programs, the same student may have different weighted scores for different programs.

In their applications, students submit a list of up to eight programs ranked from most to least preferred. Once students submit their applications, the system takes their rankings of alternatives, their program-specific scores, and the number of available seats by program, and implements a *deferred acceptance* assignment algorithm (Gale and Shapley, 1962) to determine which students are offered admission to each program.

In March of the following year, enrolled students begin their studies in their program. If stu-

[4] Eight additional institutions joined the system in 2012, but our paper focuses on earlier admission processes.

dents want to change to a different program they usually need to wait an entire year and participate in the next admission process on equal terms with other applicants.

4 Data and Sample Construction

4.1 Data Sources

This study uses a dataset that brings together administrative records on education, earnings, fertility, and marriage. To do this, we digitized hard copies of published test score results stored in a local newspaper (El Mercurio) for all students taking the standardized admission test from 1999 to 2011 and merged this information with educational, earnings, marriage and fertility data (see Appendix A for more details on data construction). We focus on students who enrolled in a university participating in SUA between 2000 and 2012 because these were the oldest cohorts for whom we could gather complete higher education records for them and their peers. Educational records for these students and their peers include: socioeconomic information that students provide when signing up to take admission tests, admission test scores, high school GPA, and university enrollment.

To measure graduation outcomes we complement this information with more recent administrative records that capture graduation for all higher institutions in the country for the 2007 to 2021 period. Because these records are only available as of 2007, when looking at graduation outcomes we focus on students who enrolled in a university participating in SUA between 2003 and 2012, whom we get to observe 10 years after they enroll for the first time.[5]

In our analysis, we have categorized programs based on their CINE-UNESCO field and divided them into two main groups: STEM and non-STEM. The STEM category includes programs in technology, engineering, physical science, math, and statistics. However, we have excluded life sciences from this category due to their higher representation of female students. Our STEM category is more aligned with what other authors have referred to as GEMP, which includes geosciences, engineering, math/computer science, and physical science (for a discussion on this, see Kahn and Ginther, 2017). Figure 1 shows the percentage of female enrollees between 2000 and 2008 and the average earnings of enrollees in 2017 for each program in each category. Although there is some variability, programs in STEM tend to have higher earnings and a male-dominated enrollment, with only 25% of their enrollees being female. In contrast, non-STEM programs typically have lower earnings and are either gender-balanced or female-dominated.

Earnings records are obtained from the unemployment insurance records of Chile's Ministry of Labor for the period between 2002 and 2017, which keeps track of the monetary contributions

[5]Since postsecondary programs in Chile are typically designed to last for five years or more, students vary rarely graduate from college in four years or less.

to the individual unemployment insurance account of each worker. When looking at earnings outcomes we focus on students who enrolled in a university participating in SUA between 2000 and 2008, whom we get to observe 10 years after they enroll for the first time. The unemployment insurance covers almost the entire formal sector, but it excludes the self-employed and public sector employees, which represent approximately 14% and 25% of individuals in our sample.[6] Earnings records from the unemployment insurance are capped at roughly $5,000 a month. In our sample, about 2% of monthly earnings for men and women are at this cap.

Fertility and marriage records were obtained from the civil registration system in 2018. For each individual in our dataset, we were able to obtain marriage records and birth records for each of their offspring. We define two individuals as partners if they married or if they have a child who was registered at birth with both of them as parents. As we do with earnings outcomes, when looking at fertility outcomes we focus on students who enrolled in a university participating in SUA between 2000 and 2008.

4.2 Sample Description

As described in the previous section, we work with two different samples of students. When looking at graduation outcomes, we focus on students who enrolled in a university program between 2003 and 2012. Instead, when looking at earnings, fertility and marriage outcomes, we focus on students who enrolled in a university program between 2000 and 2008. After dropping programs with less than 5 students, or less than 2 students of each gender, as well as those that cannot be observed for the entire period under study, we are left with a sample of 337,147 students distributed across 566 programs and 10 admission years when looking at graduation outcomes, and a sample of 281,957 students distributed across 544 programs and 9 admission years when looking at earnings, fertility and marriage outcomes.

Table 1 shows descriptive statistics for both of these samples. A little less than half of the students in our sample are women. Around 39% of students have mothers that completed tertiary education, and 42% have a father that completed tertiary education. Average labor force participation is around 45% for the mothers and 77% for the fathers of these students. The fraction of students coming from public, subsidized and private high schools (typically serving low-income families, the middle class, and the elite, respectively) are 33%, 43%, and 21%. Men and women in our sample come from similar backgrounds in terms of parental education and types of high schools, and we do not observe major differences between the 2004 to 2012 cohorts and the 2000 to 2008 cohorts.

[6] The data also excludes workers with training contracts, workers under the age of 18, those in domestic service, and pensioners. However, people in our sample should not be under these categories. Table B in the Appendix uses data from the Chilean household survey for 2017 (Casen, 2017) to characterize the percentage of individuals aged 29 to 38 who graduated from each field and who are unemployed, working in the private sector, working in the public sector, or self-employed.

Average math, language, and GPAs are almost at the 80th percentile. This is to be expected considering i) that not all students taking the test end up enrolling in college, and ii) that institutions participating in the centralized admission process typically attract higher-scoring candidates. Men tend to outperform women in math, while women have a small advantage over men in language and a larger advantage in high school GPA.

Ten years after enrolling in university, around 65% of students have graduated from any university program, while 48% have graduated from the program they initially enrolled in. Women are more likely than men to graduate from university. Regarding annual earnings (including zero earnings for the unemployed), women earn on average 8,923, whereas men earn 10,600. Additionally, 59% of women and 63% of men are employed, having worked for at least one month that year. Considering those who work, annual earnings reach 15,645 for women and 17,368 for men. Eleven years after enrolling in university, 28% of women and 22% of men have had a child, while 19% of women and 14% of men have married.

5 The Main Variable

This paper aims to estimate the impact of having high-ability male and female peers in college on students' long-term outcomes. To measure high ability, we rely on a student's rank in the distribution of the math test score in the year they took the test, which we show is highly predictive of a student's long-term outcomes. One advantage of this measure is that it avoids the reflection problem, as students take the admission test before enrolling in university. This means we do not have to worry about the possibility that peers affect a student's performance, and the student, in turn, affects their peers.

Table 2 presents the link between students' math and language test score performance, their high school GPA, and their long-term outcomes, such as graduation rates, annual earnings, employment status, fertility, and marriage.[7] Since test performance plays a crucial role in determining a student's university admission outcome, we include program and year-fixed effects. By doing so, we are able to assess whether there is a relationship between test scores and long-term outcomes after controlling for enrollment program. Additionally, we include controls for students' socioeconomic characteristics, such as parents' education and employment, family income, and head of household. Although these controls are not strictly necessary, in the sense that other students will not care about whether a student is high-ability after controlling for their parents' education, it is of interest to determine whether there exists a correlation when including such controls.

[7] As with our main results, our sample when looking at graduation outcomes includes students who enrolled in a university program between 2003 and 2012, and our sample when looking at earnings, fertility and marriage outcomes includes students who enrolled in a university program between 2000 and 2008.

As can be seen in Table 2 Panel A, there is a strong relationship between students' math test scores and their long-term outcomes, even after controlling for enrollment program and socioeconomic characteristics .For instance, for women, a 10 p.p. increase in math rank is associated with a 3.5 p.p. increase in graduation rate, a 4.3 p.p. increase in the likelihood of graduating from the program they initially enrolled in, and a 434 increase in annual earnings (which represents a 5% increase in baseline earnings). These relationships are even more pronounced for men, for whom a 10 p.p. increase in math rank is linked with a 4.5 p.p. increase in graduation rate, a 5.3 p.p. increase in the probability of graduating from the program they initially enrolled in, and a 537 increase in annual earnings (which represents a 5% increment in baseline earnings). Although GPA is also predictive of better graduation and employment outcomes, it is not as strong an indicator as math scores. Instead, language rank is not correlated with better long-term outcomes, and may even be associated with poorer outcomes for men, after accounting for program-fixed effects.

The relationship between math rank and fertility and marriage outcomes is weaker. Specifically, for women, a 10 p.p increase in math rank is correlated with a 0.006 decrease in the likelihood of having a child and a 0.003 increase in the probability of getting married 10 years after high school. Similarly, for men, a 10 p.p increase in math rank is correlated with a 0.002 p.p decrease in the probability of having a child and a 0.006 p.p increase in the probability of getting married. Although GPA is slightly more predictive of fertility and marriage outcomes, the relationship is still weak.

Table 2, Panels B and C show that the relationship between math rank and long-term outcomes is stronger for students who enroll in STEM programs compared to non-STEM programs. Specifically, for both men and women in STEM, a 10 p.p increase in math rank is associated with a 5.6 p.p higher graduation rate, an almost 7.4 p.p. increase in the likelihood of graduating from the program where they initially enrolled, and an increase of over 911 in annual earnings.

6 Empirical Strategy

6.1 Two-way fixed effects

Ou identification approach, which is common in the literature looking at peer effects, exploits variation across years and within-program in male and female peers' test scores.[8] Let y_{ijt} be the outcome of interest for student i in program j and cohort t observed ten years after college enrollment. Our base econometric specification is:

[8] This approach is common in the peer effects literature, see for instance Hoxby (2000a), Angrist and Lang (2004), Gould et al. (2009), Lavy and Schlosser (2011), Lavy et al. (2012), Black et al. (2013), Bifulco et al. (2014), Merlino et al. (2019), Cools et al. (2019) and Olivetti et al. (2020)

$$y_{ijt} = \alpha + \beta_f \cdot \bar{s}^f_{ijt} + \beta_m \cdot \bar{s}^m_{ijt} + \gamma \cdot s_{ijt} + \lambda X_{ijt} + \delta_j \cdot t + \mu_j + \eta_t + \varepsilon_{ijt}, \tag{1}$$

where s_{ijt} is our measure of individual ability for student i. Specifically, we measure ability by the student's rank in the distribution of math test scores of year t.[9] The quality of female (male) peers is represented by $\bar{s}^f_{ijt}$ ($\bar{s}^m_{ijt}$,) which corresponds to the average of s_{kjt} for every female (male) student k in program-cohort jt, excluding i. The model includes fixed effects at the program (μ_j) and cohort (η_t) levels, as well as program-specific linear time trends ($\delta_j \cdot t$). We control for individual characteristics including their parents' education and employment, their family composition, family income, test score performance (including math, language, science, and history), and gpa (X_{ijt}). Controlling for students' own math rank not only helps improve efficiency, but also eliminates the *exclusion bias* arising from the mechanical negative correlation between own test scores and the leave-out means (Caeyers and Fafchamps, 2020). Following a standard practice in the literature, we cluster standard errors at the program level. The parameters of interest, β_f and β_m, capture the effects of variation in female and male peers' quality on the outcome of interest. Appendix Tables C.5 and C.6 show that results remain consistent across various alternative specifications, including one that controls for various peer characteristics, such as the percentage of female peers, the percentage of male and female peers from private high schools, and the percentage of male and female peers whose mothers have tertiary education.

The identification strategy relies on two important assumptions. The first is that, after conditioning on program and cohort fixed effects, and individual test scores, peer assignment is as good as random. Formally, we assume:

$$\varepsilon_{ijt} \perp \bar{s}^f_{ijt}, \bar{s}^m_{ijt}$$

Students, of courses, are not randomly assigned into programs. Not only do they choose which programs to apply to, but also colleges choose among applicants whenever the number of applicants exceeds the number of available seats. Selection into programs means that students in the same program are likely to be similar in terms of both observable and unobservable characteristics. In our setting, program fixed effects control for common characteristics of all students who enroll in the same program across the years. Cohort fixed effects, on the other hand, control for common characteristics of all students who start college in the same year. The underlying assumption is that, although prospective students may choose a program based on its characteristics (including the characteristics of their students,) they cannot consider the characteristics of their specific cohort within that program, because those characteristics cannot be observed beforehand. The source of identification will then be provided by the unanticipated variation in peer group composition.

[9] We use ranks instead of test scores or other types of transformation in order to avoid problems originated in changes in test score scaling over time.

While variations of this strategy have been widely used in the education literature, most applications involve settings such as school choice in the United States in which supply-side selection typically plays a minor role. Although this is not true in our case, we have the advantage of knowing how college admission works in Chile. In particular, admission is centralized and entirely determined by students' admission test scores, making this a case of selection on observables. Hence, we account for selection coming from the supply side by including admission test scores in our regressions (i.e. math, language, history and science test scores, as well as gpa).

To support this first assumption, we estimate equation (1) using pre-determined individual characteristics as the dependent variable. Specifically, we use information on parental education, parents' labor force participation and high school type. Since these characteristics cannot be affected by variation in peers' test scores, systematically significant estimates for β_f and β_m might be an indication that peer assignment is not as good as random. The results, shown in Table 3, are consistent with quasi-random assignment of peers. All coefficients are small and, aside from a few exceptions, statistically insignificant; meaning that peers' test scores do not predict pre-determined covariates. Appendix C further shows that this balance test also works if we restrict the sample to students enrolling in STEM or non-STEM programs. In order to improve the efficiency of our estimates, our full econometric specification will control for these covariates both at the individual and peer levels. Furthermore, as discussed in the next section, the inclusion of these covariates does not significantly affect our estimates, providing further support to the empirical strategy.

The second assumption our identification strategy relies on is the constancy of the treatment effect between groups. As noted by De Chaisemartin and d'Haultfoeuille (2020), in two-way fixed effect models, estimates of β_f and β_m are obtained as weighted sums of the average treatment effects within each group/period, with weights that can be negative. While previous studies on peer effects often overlook this consideration, recent research has demonstrated that results from two-way fixed effect models may be biased if there is a correlation between the weights assigned to different groups/periods and their respective average treatment effects. To validate this second assumption, we adopt the approach of De Chaisemartin and d'Haultfoeuille (2020) and calculate the weights assigned to each group/period. In Appendix Table C.4 we present the correlations between these weights and various factors that could potentially indicate stronger treatment effects. These factors include the proportion of male students, program size, math focus (measured by the average weight assigned to the math test during student selection), and dropout rates. The results indicate that the weights are only weakly correlated with these factors, with most correlations being below 0.02.[10]

[10]Due to the continuous nature of our treatment, the estimator suggested by De Chaisemartin and d'Haultfoeuille (2020) becomes excessively noisy and uninformative in our specific context which is why we choose not to implement it.

Finally, our ability to exploit this identification strategy relies on there being sufficient residual variation in the main variable. Table 4 reports the variation in male and female peers' average math rank. For women, the average rank of male peers if 0.77, and the average rank of female peers is 0.80. Men tend to have slightly higher-performing peers, with an average rank of 0.83 for male peers and 0.81 for female peers. The standard deviation is approximately 0.13. After removing program and year fixed effects, as well as the program time trend, the residual variation is on average 0.026 for the different groups, accounting for one-fourth of the overall raw variation. Although the residual variation is slightly lower for male peers, and slightly lower for men than for women, it remains reasonably consistent across genders and both analyzed samples. Appendix C reports a similar variation in peer characteristics among students enrolling in STEM and non-STEM programs.

6.2 Robustness check: Leveraging centralized program assignment

Our two-way fixed effect approach relies on the assumption that we can adequately account for anticipated changes in group composition by controlling for program and cohort fixed effects, along with linear-time trends. However, a potential concern is that unaccounted anticipated variations within programs over time could bias our results. For example, if a program's profitability fluctuates, it may attract students with varying abilities, affecting both the quality of peers and the returns associated with program attendance. If linear-time trends fail to adequately account for these variations, our results could be biased

To address this potential threat we propose an alternative specification that takes advantage of Chile's centralized college admission system. To sketch the system, consider a set of individuals $i \in I = \{1, ..., n\}$ applying to a finite set of programs through a centralized platform. Let J = $\{1, ...J\}$ denote the set of programs indexed by j offered across all institutions. Students have preferences over programs based on a strict ordering, $\succ_i$. Programs also have preferences over applicants based on students' composite score scores s_{ijt}, that may change over time

$$s_{ijt} = \sum_{s=1}^{S} w_{jts} * s_{is} \tag{2}$$

A student is fully characterized by their type $\theta_i = (\succ_i, s_i)$. That is, the combination of an applicant's preferences and scores. We denote the set of all student types applying in year t by $\Theta_t = \bigcup_{i \in I} \theta_i$. Programs are characterized by a strictly positive capacity vector that can change over time t, $q_t = \{q_{1t}, ..., q_{tJ}\}$ and the weights that they assign to the different sections of the test $w_t = \{w_{1t}, ..., w_{Jt}\}$, which may also vary over time.

The centralized mechanism applies a deferred acceptance algorithm to generate program assignments. The inputs to the mechanism are student types Θ_t, program capacities q_t, and the weights that each program assigns to each test w_t. Let $\varphi(\Theta_t, q_t, w_t) = \mu_t$ denote the matching produced by mechanism φ for the problem (Θ_t, q_t, w_t). The matching is a function $\mu_t : \Theta_t \to J$.

The benefit of having a centralized admission system is that it takes the mystery out of treatment assignments. In our setting, we know that peer characteristics $\bar{s}^f_{ijt}$ ($\bar{s}^m_{ijt}$) are fully determined by the arguments Θ_t, q_t, w_t. Failure to control for these arguments is the only source of omitted variable bias in estimates of the causal effect of $\bar{s}^f_{ijt}$ ($\bar{s}^m_{ijt}$). Armed with precise knowledge of the source of omitted variable bias, we propose to identify causal effects by means of a conditional independence assumption.

We propose two alternative models that control for θ_i and Θ_t. Changes in capacities q_t and weights w_t, are driven by institutional needs and may not necessarily correspond with a program's expected outcomes. Typically, programs increase their capacity to boost their profits and do so discretely. Similarly, changes in weights are influenced by institutional practices and the aim to create a more or less diverse student body, also happening discretely.

Changes in Θ_t may have a more direct connection to a program's expected outcomes. If a program's admission criteria changes over time, it could impact the quality of the students in the program $\bar{s}^f_{ijt}$ ($\bar{s}^m_{ijt}$) and the characteristics of those who are admitted θ_i. Additionally, if a program becomes more profitable over time, it could influence the return of attending the program, as well as the characteristics of the student body through Θ_t. To address these issues, we propose two alternative models that account for θ_i and Θ_t. In practice, conditioning on a students' type is impractical, since there are almost as many types as students. However, we leverage the Rosenbaum and Rubin (1983) propensity score and estimate $E(\bar{s}^f|\theta_i)$, $E(\bar{s}^m|\theta_i)$; and $E(\bar{s}^f|\Theta_t)$, $E(\bar{s}^m|\Theta_t)$, where:

$$E(\bar{s}^g|\theta_i) = \frac{\sum_{t=1}^{T} E(\bar{s}^g_{ijt}|\mu_t(\theta_i, \Theta_t, q_t, w_t))}{T} \forall g \in f, m \tag{3}$$

$$E(\bar{s}^g|\Theta_i) = \frac{\sum_{t=1}^{T} E(\bar{s}^g_{ijt}|\mu_t(\Theta_i, q_t, w_t))}{T} \forall g \in f, m \tag{4}$$

In equation 3, we estimate the average quality of peers that an individual would have if they applied in each cohort while keeping their type fixed at θ_i, and allowing (Θ_t, q_t, w_t) to vary over time. We then calculate the average expected quality of male and female peers across the 2004 to 2012 period. In equation 4, we estimate the average quality of peers that an individual would have if they applied in each year, while keeping the preferences of all individuals in their cohort fixed, and allowing q_t, w_t to vary over time. Again, we calculate the average expected quality of male and female peers over the 2004 to 2012 period.

Intuitively, our two-way fixed effect model compares students who enroll in the same program over time. By including controls for $E(\bar{s}^g|\theta_i)$ we are comparing students who enroll in the same program and share the same type θ_i, meaning they have the same preferences and scores. By including controls for $E(\bar{s}^g|\Theta_i)$ we take a step further and compare individuals who not only enroll in the same program and share the same type, but who also apply in years where other student preferences are the same (Θ_i). For this group, any variation in peer characteristics across time is solely due to variations in q_t and/or w_t.

Given that the admission system underwent some minor changes in 2004 (with students now required to choose between two subjects, as opposed to six prior to that year), when implementing this alternative specification we focus on students who participated in SUA between 2004 and 2012. Because of this, we limit our analysis to graduation outcomes when using this alternative specification.

7 Results

This section estimates the long-term effects of college peers, organizing the results by outcome, beginning with college graduation, then labor market outcomes, and ending with fertility and marriage.

7.1 Effects of Peer Ability on College Graduation

We begin by studying the effect of peers on college graduation. Table 5 reports estimates of the effect of male and female peers' average math rank on students' likelihood of graduating from a university program. Specifically, we examine three probabilities: graduating from any university program, graduating on-time (i.e., within 7 years of high school graduation[11]), and graduating from the program they first enrolled in. Ten years after high school, on average, 71% of the individuals in our sample have graduated from a university program, 48% have graduated on time, and 55% have graduated from the program where they first enrolled.

Panel A of Table 5 presents our results across different fields. Our findings reveal that having higher-performing female peers has a positive impact on women's probability of graduating from any university program. However, the effect is small in magnitude. Increasing the quality of female peers in one standard deviation (2.7 p.p.) increases women's probability of graduating from any university program by 0.4 p.p.

In contrast, when we focus on women in STEM programs, the results are much stronger. Women in STEM benefit significantly from having better female peers, but they are also negatively affected by the presence of better male peers. Increasing female peer quality in one standard deviation increases women's probability of graduating from any university program by 0.8 p.p.

[11]We choose this threshold because programs included in our sample last at most 7 years

Conversely, increasing male peer quality in one standard deviation decreases women's probability of graduating from the STEM program they chose by 1.1 p.p. and their probability of graduating on-time by 0.9 p.p.These values represent a 3.4% and 3.1% decrease in baseline probabilities, respectively.

In terms of women enrolling in non-STEM fields, our analysis shows that the characteristics of peers are not as significant, and we cannot reject a null-effect. As for men, our results indicate that they are not affected by the quality of their male or female peers, regardless of their field of study.

Table 6 presents the results of our analysis using an alternative specification, which controls for $E(p_i|\theta_i)$ and $E(p_i|\Theta_i)$ (allowing these effects to vary at the program level). Because the number of optional tests students has to choose from decreased in 2004, we limit our sample to the 2004 to 2012 cohorts for this strategy. Columns 1, 4, 7 and 10 of Table 6 show the results of our two-way fixed effects specification. Columns 2, 5, 8, and 11 control for $E(p_i|\theta_i)$, while columns 3, 6, 9 and 12 control for $E(p_i|\Theta_i)$. Our main findings remain robust across all specifications. Specifically, we find strong and consistent evidence that having better female peers has a positive effect on the graduation outcomes of women in STEM, while having better male peers has a negative effect. These results hold across all specifications, indicating the robustness of our findings.

To gain further insights into our findings, we examine alternative measures of peer quality in Table 7. Columns 1, 4, 7, and 8 present the effects of the average rank of male and female peers on graduation outcomes. Pooling all peers together reveals no discernible impact of peer quality on graduation outcomes for both men and women. This result is not surprising since the effects of male and female peer quality operate in opposite directions for women. Moving on, columns 2, 5, 8, and 10 utilize the percentage of male and female peers in the lowest quartile of math performance within the program (where we estimate quartiles based on the entire cohort of program enrollees across time). Conversely, columns 3, 6, 9, and 12 employ the percentage of male and female peers in the upper quartile of math performance within the program. Although our estimates become noisier with these alternative specifications, they suggest that the presence of poorly performing female peers negatively impacts women in STEM, while the presence of high-performing female peers benefits them. Similarly, the presence of low-performing male peers benefits women in STEM, while the presence of high-performing male peers harms them. These findings indicate that it is not solely the performance of high or low performing peers that have the greatest impact, which supports our decision to use average peer performance as our measure of peer quality.

7.2 Effects of Peer Ability on Labor Market Outcomes

We next investigate how peer quality affects students' labor market outcomes. While we have established that peer quality affects the likelihood of women in STEM graduating from a university program, graduating on time, and graduating from their program of choice, the effect on labor market outcomes remains uncertain. Although it is reasonable to assume that an increase (decrease) in overall or on-time graduation would have a positive (negative) impact on earnings, the influence of program graduation on labor market outcomes is less clear. Students may switch to higher or lower return programs based on better peers. For example, women in STEM may opt for business programs that offer high earnings prospects. Furthermore, even if peers do not directly influence graduation probability, they may still affect labor market outcomes. This could be due to their impact on other graduation outcomes that we are unable to measure, such as GPA or program specialization, or because they continue to affect students beyond college as an essential network and reference group (as discussed in Section 2).

Table 8 presents estimates of the effect of the average math rank of male and female peers on various labor market outcomes, including the probability of being employed for at least one month per year, annual earnings (including zero earnings for the unemployed), annual earnings conditional on having worked for at least one month, the number of accumulated months of work experience, and the total number of employers ten years after high school. At this point in time, approximately 60% of individuals in our sample are employed, with around 2 years of work experience and having had more than 4 different employers. Conditional on having worked at least one month, women's annual earnings are $15,365, while men's annual earnings are $17,055.

Panel A of Table 8 presents our findings across different fields. We observe a positive, albeit non-significant, effect of having better female peers on women's earnings, driven by an increase in employment probability, accumulated experience, and number of employers. There is also a slight increase in earnings conditional on being employed. On the other hand, better male peers have a negative and significant effect on women's earnings. An increase in male peer quality by one standard deviation reduces baseline earnings by approximately 0.5%. This decrease is due to a decrease in employment probability and accumulated experience, as well as lower earnings among employed women.

Although our results are subject to some noise, we observe that the effect is particularly strong for women in STEM, as shown in Table 8 panel B. Although we cannot reject the null hypothesis of no effect, our estimates suggest that improving the quality of female peers by one standard deviation could boost earnings by around 0.5%. In contrast, raising the quality of male peers by one standard deviation could lead to a reduction in baseline earnings of approximately 1%.

Consistent with previous findings, we find that the presence of better male or female peers does not have a significant impact on men's earnings. If anything, we observe that men's earnings are negatively affected by the presence of higher-performing male peers, especially in STEM fields.

7.3 Effects of Networks on Labor Market Outcomes

In this section, we examine the effect of peer quality on the probability of working at an alumni-affiliated firm. However, before delving into causal estimates, we first provide descriptive evidence on the significance of peer connections in shaping labor market outcomes for both men and women in STEM and non-STEM fields.

To analyze the importance of college peers on labor market outcomes, we look at the probability of two graduates from the same program working at the same firm in 2017.[12] We investigate this probability across stem and non-stem programs, while also considering whether the peers are of the same sex or not. Additionally, we compare the probability of two individuals who attended the same program at the same time working at the same firm to that of two individuals who attended the same program at different times, in order to understand the role of networks in explaining the results. The intuition is that same-cohort pairs within a program are similar to pairs of students a few years apart in terms of pre-college backgrounds and institutional inputs, but same-cohort pairs are more likely to know each other and have mutual contacts. If students obtain jobs through contacts or if individuals are more productive when working with someone they know, college peers may be more likely to work at the same firms than other pairs of similar students. A similar strategy is used by Zimmerman (2019) to study the importance of peer ties in reaching leadership positions.

We can draw three important conclusions from Figure 2. First, in both stem and non-stem programs, same-sex female peers have a higher probability of working together in the same firm than same-sex male peers or different-sex peers, regardless of whether they attended college at the same time or not. This suggests that women tend to concentrate on fewer firms than men, even within the same field of study. Second, the probability of working in the same firm is notably higher for women who graduate from STEM programs. In fact, women who graduate from STEM programs are almost twice as likely to work in the same firm as a same-sex peer than men who graduate from STEM. They are also more likely to work in the same firm than their female peers when compared to women who graduate from non-STEM programs. Third, the probability of working together is particularly high for women in STEM who attended the same program at the same time. This suggests that networks play an important role in explaining the high likelihood of female STEM graduates working together.

To gain deeper insights into the extent to which access to higher-quality peers might provide individuals with an improved professional network, we examine the impact of peers on the likelihood of working at a firm affiliated with other program alumni. Specifically, we define an ap-

[12]Our sample consists of individuals who were employed in 2017. However, we have excluded public sector employees since we cannot determine the specific organization within the public sector where these individuals are employed. Additionally, we have excluded individuals in the health sector, as a majority of them work in the public sector.

plicant as having secured a job at an alumni firm if, at any point between 2002 and 2017, the firm employed another graduate from the program (considering individuals who graduated from each program between 2007 and 2021). It is worth noting that all our network outcomes are "leave-individual-out," meaning that even if the applicant themselves graduated from the program, the corresponding variable is only assigned a value of one if another alumnus is associated with that firm. Additionally, our variable definitions allow applicants to be either beneficiaries or benefactors of alumni networks. In other words, an applicant could work at an alumni firm either through receiving a job referral from an alumnus or by referring an alumnus to the firm.

In Table 9, we show how peer quality influences the probability of working at a firm that employs at least one of the following: alumni, female alumni, male alumni, high-performing female alumni, or high-performing male alumni. We define a high-performing alumnus as a student who graduated from the program and whose math rank exceeds the average rank of students enrolling in that program throughout the entire study period.

Results indicate that 27% of individuals, ten years after high school graduation, are working at a firm affiliated with other program alumni. As expected, women exhibit a higher likelihood than men of working at a firm affiliated with a female alumna, while men are more likely to work at a firm affiliated with a male alumnus. However, when examining the impact of peer quality on the probability of working at an alumni firm, we find no discernible effects for women. In contrast, for men, the results indicate that having more accomplished male peers actually decreases the likelihood of working at a firm affiliated with a male alumnus, particularly in cases where the firm employs highly accomplished male alumni. This finding challenges the notion that having more successful male peers grants men enhanced access to a professional network that significantly influences their earnings. If anything, it suggests that men may be negatively affected by the presence of highly accomplished male peers, particularly in STEM fields. This aligns with the concept that when individuals have higher-performing male peers, the immediate professional market becomes more competitive, making it more challenging to distinguish oneself and stand out from the crowd.

7.4 Effects of Peer Ability on Fertility and Marriage

Finally, we examine the effect of peer quality on fertility and marriage outcomes for both men and women. In Table 10, we present estimates of the impact of male and female peers' average math rank on the probability of having children and the number of children for students. We include individuals who completed high school between 1999 and 2009 and examine the probability of having a child after 10 years of high school graduation, around the age of 28.

In our sample, 17% of women and 13% of men have had a child 10 years after high school. Having better male or female peers in college does not affect the probability of having children when we look across fields.[13] However, for women in STEM, we find that better female peers decrease their probability of having a child and the number of children they have had by age 28. Conversely, having better male peers increases the probability of having a child and the number of children that women have had by age 28. Results are statistically significant, with the number of children decreasing by approximately 3.6% for a one-standard-deviation increase in the quality of female peers and increasing by approximately 4.2% for a one-standard-deviation increase in the quality of male peers

Figure 3 examines how fertility effects evolve over time for men and women in STEM. The blue line represents the baseline probability of having a child at each age, while the red line shows the probability for those exposed to an average rank of male or female peers that is 0.1 higher. The coefficients are estimated using our baseline specification. While we observe outcomes for our full sample up to 10 years after high school graduation, we can only observe outcomes 18 years after high school graduation for individuals who completed high school before 2002. Therefore, our estimates become noisier over time as we lose observations. By age 36, 42% of women and 38% of men in our sample have had children. The effect of having better female peers decreases the probability of having children for women, and the effect remains constant through the period we observe. In contrast, the effect of having better male peers increases the probability of having a child for women between 9 and 12 years out of high school, but the effect disappears after that, suggesting that better male peers increase the probability of having a child earlier, but not overall by the age of 36.

Moving on to Table 11, we investigate he impact of peer quality on marriage market outcomes. We include individuals who completed high school between 1999 and 2007 and examine their probability of being married and spouse characteristics after 12 years of high school graduation, around the age of 30. Our results reveal no significant effect of having better male or female peers on men's or women's likelihood of getting married or having a spouse by the age of 30.

We also investigate whether having better male or female peers affects the probability of marrying someone from the same program. Interestingly, we find that for men, having better female peers slightly increases their probability of marrying someone from their same program, while having better male peers slightly decreases this probability. However, for women, we do not observe any effect of having better male or female peers on their probability of marrying someone from the same program.

Moreover, we examine the impact of peer quality on spouse characteristics for those individuals who have a spouse. We look at their annual earnings, as well as their math, language, and GPA scores, where available. Our results indicate that having better female peers increases the annual earnings of women's spouses. For women in STEM, we also find that better female peers increase

[13] We find that better female peers slightly increase men's probability of having a child, but results are small in magnitude.

the math ability of their spouses. On the other hand, for men, having better female peers slightly increases the earnings and test score performance of their spouses.

The results concerning men support the notion that having access to a higher-quality network of peers of the opposite sex can potentially enhance marriage market offers. Conversely, for women, the impact of having access to a better network of peers of the opposite sex does not follow the same pattern. While there may be a positive effect associated with having access to a superior network of male peers, this effect appears to be offset by a negative influence stemming from the higher achievement levels of these male peers, which can, in turn, affect graduation outcomes and subsequently impact marriage market outcomes.

7.5 Is it STEM that makes a difference?

Our findings indicate that women in STEM fields are particularly negatively affected by the presence of high-performing male peers. However, it is crucial to explore whether this effect is solely driven by STEM programs themselves or if other correlated program characteristics contribute to the observed outcomes. To address this, we analyze heterogeneous effects across various program characteristics, such as program gender composition, selectivity, and dropout rates, as presented in Table 12. This analysis enables us to gain a comprehensive understanding of the factors influencing the observed effects.

We begin by categorizing programs based on their gender composition, distinguishing between male-dominated and female-dominated programs. We define male-dominated programs as those with more than 60% male enrollees, while female-dominated programs have more than 60% female enrollees. It is worth noting that although the majority of STEM programs fall under the male-dominated category using this criterion, it is essential to acknowledge that approximately 21% of STEM programs do not exhibit male dominance. Furthermore, a substantial proportion of male-dominated programs (18%) are non-STEM, indicating that the overlap between male dominance and STEM fields is not absolute. In our analysis, as depicted in Table 12, we find no compelling evidence that women are disproportionately affected by the presence of high-performing male peers in male-dominated programs once we consider the inclusion of non-STEM programs.

In terms of program selectivity, we divide programs into two groups based on whether the average math performance of their enrollees is above or below the average across all programs. According to this categorization, 66% of STEM programs are considered selective, while 34% are non-selective. However, we do not observe heterogeneous effects along this dimension.

Finally, we divide programs into two groups based on whether the average dropout rate is above or below the average across all programs. Under this classification, 74% of STEM programs have high dropout rates, while 26% have low dropout rates. Similar to the other dimensions, we do not observe heterogeneous effects in relation to dropout rates.

These results suggest that it is STEM programs what really make a difference. This programs tend to be male-dominated, more selective and have high dropout rates, but above all of that these are areas that have been historically dominated by men and were women have traditionally had a hard time advancing.

8 Conclusion

This paper provides valuable insights into the long-term effects of college peers on the outcomes of both men and women. Our results reveals that the quality of peers significantly impacts women's academic choices, labor market outcomes, fertility, and marriage market outcomes. Using nationwide data from higher education in Chile, and exploiting variation across cohorts and within programs, we show that the ability of peers can significantly affect outcomes for women by age 28. Exposure to higher-performing peers of the same sex increases college graduation, labor market outcomes, marriage market outcomes, and reduces fertility. However, exposure to better peers of the opposite sex decreases college graduation, labor market outcomes, and marriage market outcomes. These effects are primarily driven by women attending STEM programs.

From a policy perspective, this paper suggests that investing in female human capital can have a greater impact on advancing gender equality than traditionally assumed, as the multiplier effects that propagate through women's networks of female peers can be significant. Furthermore, our research highlights the extent to which highly competitive, male-dominated environments can hinder women from advancing.

References

Ahn, T., Arcidiacono, P., Hopson, A., and Thomas, J. R. (2019). Equilibrium grade inflation with implications for female interest in stem majors. Technical report, National Bureau of Economic Research.

Anelli, M. and Peri, G. (2019). The effects of high school peers' gender on college major, college performance and income. *The Economic Journal*, 129(618):553–602.

Angrist, J. D. and Lang, K. (2004). Does School Integration Generate Peer Effects? Evidence from Boston's Metco Program. *American Economic Review*, 94(5):1613–1634.

Bertrand, M., Kamenica, E., and Pan, J. (2015). Gender identity and relative income within households. *The Quarterly Journal of Economics*, 130(2):571–614.

Bifulco, R., Fletcher, J. M., Oh, S. J., and Ross, S. L. (2014). Do High School Peers Have Persistent Effects on College Attainment and Other Life Outcomes. *Labour Economics*, 29:83–90.

Black, S. E., Devereux, P. J., and Salvanes, K. G. (2013). Under pressure? The effect of peers on outcomes of young adults. *Journal of Labor Economics*, 31(1):119–153.

Booth, A. and Nolen, P. (2012a). Choosing to compete: How different are girls and boys? *Journal of Economic Behavior & Organization*, 81(2):542–555.

Booth, A. L. and Nolen, P. (2012b). Gender differences in risk behaviour: does nurture matter? *The economic journal*, 122(558):F56–F78.

Bostwick, V. K. and Weinberg, B. A. (2022). Nevertheless she persisted? gender peer effects in doctoral stem programs. *Journal of Labor Economics*, 40(2):397–436.

Brenøe, A. A. and Zölitz, U. (2020). Exposure to more female peers widens the gender gap in stem participation. *Journal of Labor Economics*, 38(4):1009–1054.

Bursztyn, L., Fujiwara, T., and Pallais, A. (2017). 'acting wife': Marriage market incentives and labor market investments. *American Economic Review*, 107(11):3288–3319.

Caeyers, B. and Fafchamps, M. (2020). Exclusion bias in the estimation of peers effects. *NBER Working Paper Series*.

Calkins, A., Binder, A., Shaat, D., and Timpe, B. (2020). *When Sarah Meets Lawrence: The Effect of Coeducation on Women's Major Choices*. RAND.

Carrell, S. E., Fullerton, R. L., and West, J. E. (2009). Does your Cohort Matter? Measuring Peer Effects in College Achievement. *Journal of Labor Economics*, 27(3):439–464.

Cools, A., Fernández, R., and Patacchini, E. (2019). Girls, Boys, and High Achievers.

De Chaisemartin, C. and d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–2996.

Feld, J. and Zölitz, U. (2022). The effect of higher-achieving peers on major choices and labor market outcomes. *Journal of Economic Behavior & Organization*, 196:200–219.

Fischer, S. (2017). The downside of good peers: How classroom composition differentially affects men's and women's stem persistence. *Labour Economics*, 46:211–226.

Foster, G. (2006). It's Not your Peers, and it's Not your Friends: Some Progress Toward Understanding the Educational Peer Effect Mechanism. *Journal of Public Economics*, 90(8-9):1455–1475.

Gale, D. and Shapley, L. S. (1962). College admissions and the stability of marriage. *The American Mathematical Monthly*, 69(1):9–15.

Gneezy, U., Leonard, K. L., and List, J. A. (2009). Gender differences in competition: Evidence from a matrilineal and a patriarchal society. *Econometrica*, 77(5):1637–1664.

Goulas, S., Megalokonomou, R., and Zhang, Y. (2018). Does the girl next door affect your academic outcomes and career choices? *Available at SSRN 3286169*.

Gould, E. D., Lavy, V., and Paserman, M. D. (2009). Does immigration affect the long-term educational outcomes of natives? Quasi-experimental evidence. *The Economic Journal*, 119(540):1243–1269.

Hampole, M., Truffa, F., and Wong, A. (2021). Peer effects and the gender gap in corporate leadership: Evidence from mba students. Technical report, Working Paper.

Han, L. and Li, T. (2009). The Gender Difference of Peer Influence in Higher Education. *Economics of Education Review*, 28(1):129–134.

Hayashi, R. (2016). Peer Effects in Academic Performance. *SSRN Electronic Journal*, (979).

Hill, A. J. (2015). The girl next door: The effect of opposite gender friends on high school achievement. *American Economic Journal: Applied Economics*, 7(3):147–77.

Hitsch, G. J., Hortaçsu, A., and Ariely, D. (2010). Matching and sorting in online dating. *American Economic Review*, 100(1):130–163.

Hoxby, C. M. (2000a). Peer Effects in the Classrom: Learning From Gender and Race Variation. *NBER Working Paper Series*.

Hoxby, C. M. (2000b). The Effects of Class Size on Student Achievement: New Evidence from Population Variation. *The Quarterly Journal of Economics*, (November):1239–1285.

Kamas, L. and Preston, A. (2012). The importance of being confident; gender, career choice, and willingness to compete. *Journal of Economic Behavior & Organization*, 83(1):82–97.

Kremer, M. and Levy, D. (2008). Peer Effects and Alcohol Use College Students among. *The Journal of Economic Perspectives*, 22(3):189–206.

Lavy, V., Paserman, M. D., and Schlosser, A. (2012). Inside the Black Box of Ability Peer Effects: Evidence from Variation in the Proportion of Low Achievers in the Classroom. *The Economic Journal*, 122(559):208–237.

Lavy, V. and Schlosser, A. (2011). Mechanisms and Impacts of Gender Peer Effects at School. *American Economic Journal: Applied Economics*, 3(2):1–33.

Lim, J. and Meer, J. (2020). Persistent effects of teacher–student gender matches. *Journal of Human Resources*, 55(3):809–835.

Lyle, D. S. (2007). Estimating and Interpreting Peer and Role Model Effects from Randomly Assigned Social Groups at West Point. *The Review of Economics and Statistics*, 89(2):289–299.

Merlino, L. P., Steinhardt, M. F., and Wren-Lewis, L. (2019). More than just friends? School peers and adult interracial relationships. *Journal of Labor Economics*, 37(3):663–713.

Mouganie, P. and Wang, Y. (2020). High-performing peers and female stem choices in school. *Journal of Labor Economics*, 38(3):805–841.

Niederle, M. and Vesterlund, L. (2007). Do women shy away from competition? do men compete too much? *The quarterly journal of economics*, 122(3):1067–1101.

Niederle, M. and Vesterlund, L. (2008). Gender differences in competition. *Negotiation Journal*, 24(4):447–463.

Olivetti, C., Patacchini, E., and Zenou, Y. (2020). Mothers, Peers, and Gender-Role Identity. *Journal of the European Economic Association*, 18(1):266–301.

Ost, B. (2010). The role of peers and grades in determining major persistence in the sciences. *Economics of Education Review*, 29(6):923–934.

Rask, K. and Tiefenthaler, J. (2008). The role of grade sensitivity in explaining the gender imbalance in undergraduate economics. *Economics of Education Review*, 27(6):676–687.

Sacerdote, B. (2001). Peer Effects with Random Assignment: Results for Dartmouth Roommates. *The Quarterly Journal of Economics*, 116(2):681–704.

Schneeweis, N. and Zweimüller, M. (2012). Girls, girls, girls: Gender composition and female school choice. *Economics of Education review*, 31(4):482–500.

Stinebrickner, R. and Stinebrickner, T. R. (2006). What Can be Learned about Peer Effects Using College Roommates? Evidence from New Survey Data and Students from Disadvantaged Backgrounds. *Journal of Public Economics*, 90(8-9):1435–1454.

Thomas, M. (2021). Effects of peer groups on the gender-wage gap and life after the mba: Evidence from the random assignment of mba peers. *Available at SSRN 3968529*.

Zhang, L. and Pu, S. (2017). It Takes Two Shining Lights to Brighten the Room: Peer Effects with Random Roommate Assignments. *Education Economics*, 25(1):3–21.

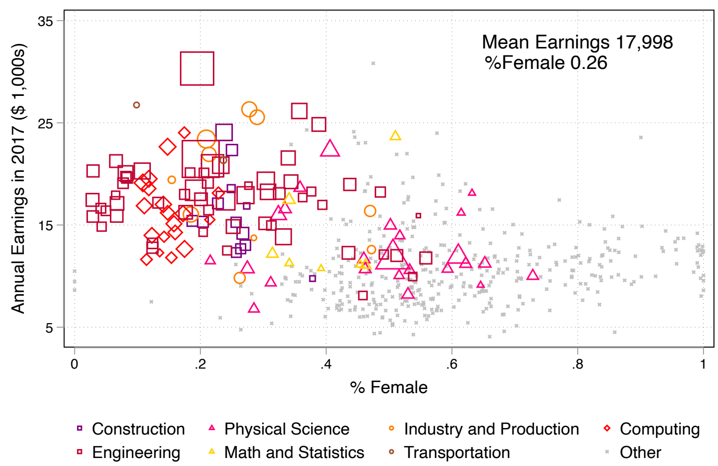
Zimmerman, D. J. (2003). Peer Effects in Academic Outcomes: Evidence From a Natural Experiment. *Review of Economics and Statistics*, 85(1):9–23.

Zimmerman, S. D. (2019). Elite colleges and upward mobility to top jobs and top incomes. *American Economic Review*, 109(1):1–47.

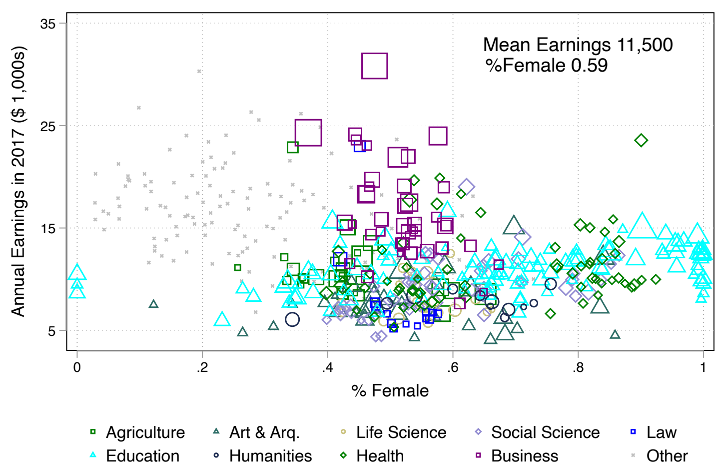
Zölitz, U. and Feld, J. (2021). The effect of peer gender on major choice in business school. *Management Science*, 67(11):6963–6979.

9 Figures and Tables

Figure 1: Mean Earnings and Women Participation by Program and Field



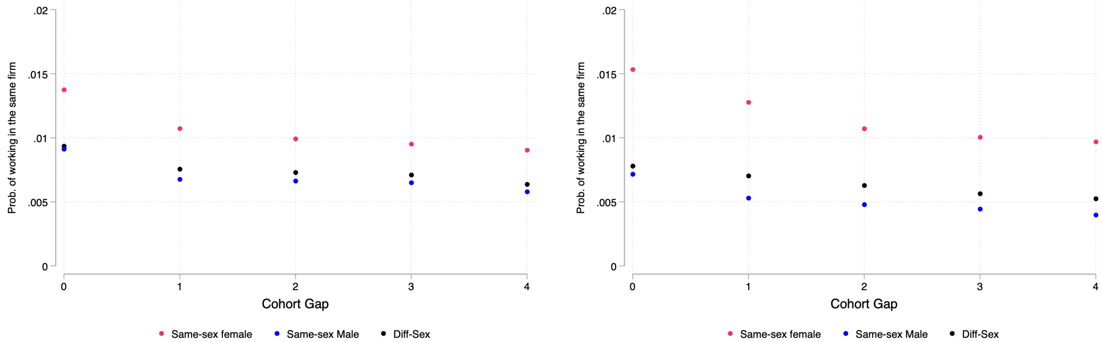
(a) STEM



(b) Non-STEM

Notes:

Figure 2: Co-workers by cohort distance

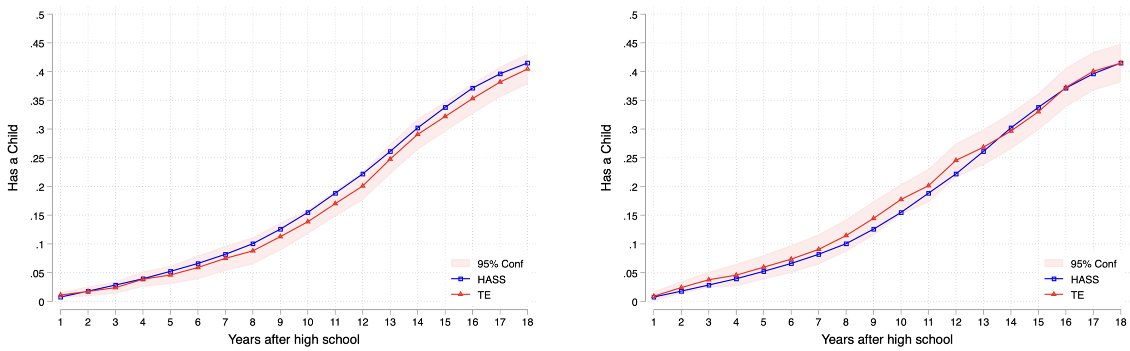


(a) Non-STEM

(b) STEM

Notes:

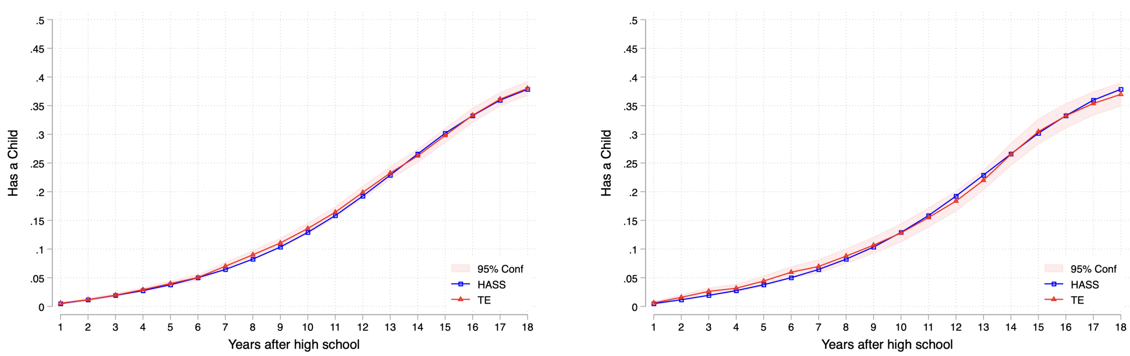
Figure 3: Peer effects on Fertility



High-achieving female peers

High-achieving male peers

(a) Women



High-achieving female peers

High-achieving male peers

(b) Men

Table 1: Descriptive Statistics

	2003-2012 Cohorts						2000-2008 Cohorts					
	Women			Men			Women			Men		
	mean	s.d.	obs.	mean	s.d.	obs.	mean	s.d.	obs.	mean	s.d.	obs.
Cohort Characteristics												
Cohort Size	85.652	78.156	161,007	111.012	121.067	176,140	86.357	77.110	133,951	115.903	115.879	148,006
Socioeconomic Characteristics												
Mother primary ed	0.111	0.315	161,007	0.100	0.300	176,140	0.117	0.321	133,951	0.111	0.314	148,006
Mother secondary ed	0.440	0.496	161,007	0.442	0.497	176,140	0.434	0.496	133,951	0.440	0.496	148,006
Mother tertiary ed	0.389	0.488	161,007	0.392	0.488	176,140	0.395	0.489	133,951	0.392	0.488	148,006
Father primary ed	0.109	0.311	161,007	0.095	0.293	176,140	0.109	0.312	133,951	0.098	0.298	148,006
Father secondary ed	0.363	0.481	161,007	0.361	0.480	176,140	0.354	0.478	133,951	0.351	0.477	148,006
Father tertiary ed	0.401	0.490	161,007	0.422	0.494	176,140	0.422	0.494	133,951	0.439	0.496	148,006
Mother works	0.460	0.498	161,007	0.461	0.498	176,140	0.449	0.497	133,951	0.447	0.497	148,006
Father works	0.753	0.431	161,007	0.766	0.423	176,140	0.770	0.421	133,951	0.784	0.411	148,006
Mother works fulltime	0.380	0.485	161,007	0.383	0.486	176,140	0.381	0.486	133,951	0.380	0.485	148,006
Father works fulltime	0.595	0.491	161,007	0.624	0.484	176,140	0.624	0.484	133,951	0.654	0.476	148,006
Public school	0.320	0.466	159,046	0.316	0.465	173,523	0.344	0.475	130,637	0.346	0.476	144,070
Voucher school	0.471	0.499	159,046	0.441	0.497	173,523	0.416	0.493	130,637	0.381	0.486	144,070
Private school	0.188	0.391	159,046	0.215	0.411	173,523	0.219	0.414	130,637	0.244	0.430	144,070
Academic Performance												
Math rank	0.774	0.168	161,007	0.831	0.150	176,140	0.777	0.166	133,951	0.831	0.148	148,006
GPA rank	0.785	0.196	161,007	0.704	0.237	176,140	0.780	0.201	133,951	0.685	0.247	148,006
Language rank	0.793	0.170	161,007	0.787	0.179	176,140	0.788	0.174	133,951	0.784	0.183	148,006
Graduation												
Graduates Univ	0.715	0.452	161,007	0.579	0.494	176,140						
Graduates Program	0.553	0.497	161,007	0.401	0.490	176,140						
Earnings and Employment												
Annual Earnings							8,923	11,637	131,700	10,600	13,308	145,426
Months worked a year							0.588	0.492	133,951	0.628	0.483	148,006
Fertility and Marriage												
Has child							0.275	0.447	131,700	0.219	0.414	145,426
Married							0.186	0.389	131,700	0.136	0.343	145,426

Notes: The Table displays means, standard deviations and number of observations for all the cohorts enrolling between 2003 and 2012 and between 2000 and 2008.

Table 2: Test Scores, GPA and Long-term Outcomes

	Women						Men					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Grad. Univ	Grad Program	Annual Earnings	Months Worked	Has Child	Married	Grad. Univ	Grad Program	Annual Earnings	Months Worked	Has Child	Married
All												
Math rank	0.35***	0.43***	4,341***	0.07***	−0.06***	0.03***	0.45***	0.53***	5,370***	0.04***	0.02	0.06***
	(0.01)	(0.01)	(299.0)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(363.7)	(0.01)	(0.01)	(0.01)
GPA rank	0.34***	0.34***	3,626***	0.04***	−0.12***	0.02***	0.36***	0.32***	4,022***	0.02***	−0.06***	0.03***
	(0.01)	(0.01)	(183.1)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(161.3)	(0.01)	(0.01)	(0.00)
Lang rank	0.00	0.01	−379.4	−0.04***	−0.06***	0.01	−0.00	−0.00	−971.1***	−0.06***	−0.07***	0.02**
	(0.01)	(0.01)	(270.6)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(268.1)	(0.01)	(0.01)	(0.01)
Mean dependent variable	0.71	0.55	8,923	0.59	0.28	0.19	0.58	0.40	10,600	0.63	0.22	0.14
N. Obs.	161,007	161,007	131,700	133,951	131,700	131,700	176,140	176,140	145,426	148,006	145,426	145,426
STEM												
Math rank	0.52***	0.75***	9,819***	0.13***	−0.10***	−0.04	0.59***	0.73***	8,402***	0.06**	−0.01	0.07***
	(0.03)	(0.03)	(1,082)	(0.04)	(0.04)	(0.03)	(0.02)	(0.02)	(751.3)	(0.02)	(0.02)	(0.02)
GPA rank	0.47***	0.37***	6,640***	0.10***	−0.15***	0.00	0.38***	0.31***	5,708***	0.05***	−0.05***	0.04***
	(0.02)	(0.02)	(543.5)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(278.6)	(0.01)	(0.01)	(0.01)
Lang rank	−0.01	−0.02	−451.1	−0.04*	−0.07***	0.02	−0.03**	−0.02	−1,469***	−0.08***	−0.09***	0.02**
	(0.02)	(0.02)	(708.5)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(421.6)	(0.01)	(0.01)	(0.01)
Mean dependent variable	0.64	0.32	11,546	0.65	0.24	0.17	0.55	0.29	13,810	0.71	0.22	0.14
N. Obs.	28,088	28,088	21,860	22,210	21,860	21,860	82,068	82,068	63,598	64,798	63,598	63,598
Non-STEM												
Math rank	0.33***	0.39***	3,685***	0.06***	−0.05***	0.04***	0.38***	0.43***	3,921***	0.03**	0.03**	0.06***
	(0.01)	(0.01)	(304.6)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(385.6)	(0.02)	(0.01)	(0.01)
GPA rank	0.32***	0.33***	3,089***	0.03***	−0.12***	0.03***	0.36***	0.34***	2,825***	−0.01	−0.07***	0.03***
	(0.01)	(0.01)	(192.1)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(189.1)	(0.01)	(0.01)	(0.01)
Lang rank	−0.00	0.00	−415.9	−0.04***	−0.06***	0.01	0.02	0.01	−647.0*	−0.05***	−0.05***	0.01
	(0.01)	(0.01)	(291.9)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(342.8)	(0.02)	(0.01)	(0.01)
Mean dependent variable	0.73	0.60	8,401	0.58	0.28	0.19	0.61	0.49	8,105	0.57	0.22	0.13
N. Obs.	132,919	132,919	109,840	111,741	109,840	109,840	94,072	94,072	81,828	83,208	81,828	81,828

Notes:

Table 3: Balance Test

	2003-2013 Cohorts				2000-2008 Cohorts			
	Women		Men		Women		Men	
Variable	Mean rank of female peers (1)	Mean rank of male peers (2)	Mean rank of female peers (3)	Mean rank of male peers (4)	Mean rank of female peers (5)	Mean rank of male peers (6)	Mean rank of female peers (7)	Mean rank of male peers (8)
Mother primary ed	−0.04	−0.02	0.04	0.06	−0.07	0.01	0.01	0.04
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)
	[153,664]	[153,664]	[166,906]	[166,906]	[130,692]	[130,692]	[143,900]	[143,900]
Mother secondary ed	−0.04	0.08^{**}	0.00	0.00	0.04	0.05	−0.03	0.03
	(0.05)	(0.04)	(0.05)	(0.06)	(0.06)	(0.04)	(0.05)	(0.06)
	[153,664]	[153,664]	[166,906]	[166,906]	[130,692]	[130,692]	[143,900]	[143,900]
Mother tertiary ed	0.06	-0.07^{*}	−0.06	−0.04	0.03	−0.07	0.01	−0.06
	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.06)
	[153,664]	[153,664]	[166,906]	[166,906]	[130,692]	[130,692]	[143,900]	[143,900]
Father primary ed	−0.04	−0.01	0.04	0.00	−0.02	−0.01	0.02	0.03
	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
	[153,664]	[153,664]	[166,906]	[166,906]	[130,692]	[130,692]	[143,900]	[143,900]
Father secondary ed	−0.01	0.06	−0.03	−0.02	−0.04	0.08	−0.02	−0.04
	(0.05)	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.07)
	[146,486]	[146,486]	[160,610]	[160,610]	[123,703]	[123,703]	[137,549]	[137,549]
Father tertiary ed	0.01	−0.03	−0.02	0.00	0.05	−0.08	−0.00	−0.06
	(0.05)	(0.04)	(0.04)	(0.05)	(0.06)	(0.05)	(0.05)	(0.07)
	[146,486]	[146,486]	[160,610]	[160,610]	[123,703]	[123,703]	[137,549]	[137,549]
Mother works	0.01	0.03	−0.03	−0.02	−0.03	0.01	−0.04	0.01
	(0.05)	(0.05)	(0.04)	(0.06)	(0.06)	(0.05)	(0.05)	(0.07)
	[153,163]	[153,163]	[166,437]	[166,437]	[130,167]	[130,167]	[143,406]	[143,406]
Father works	−0.01	0.01	−0.02	0.03	0.04	−0.01	0.01	−0.01
	(0.04)	(0.03)	(0.03)	(0.04)	(0.05)	(0.03)	(0.04)	(0.05)
	[142,880]	[142,880]	[157,312]	[157,312]	[121,035]	[121,035]	[135,111]	[135,111]
Mother works fulltime	0.01	0.03	−0.04	−0.02	−0.05	0.01	0.00	−0.02
	(0.05)	(0.05)	(0.04)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)
	[153,163]	[153,163]	[166,437]	[166,437]	[130,167]	[130,167]	[143,406]	[143,406]
Father works fulltime	0.01	0.01	-0.08^{*}	0.04	−0.01	−0.01	−0.02	−0.06
	(0.05)	(0.05)	(0.04)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)
	[142,880]	[142,880]	[157,312]	[157,312]	[121,035]	[121,035]	[135,111]	[135,111]
Public school	−0.00	0.06	0.05	0.12^{**}	0.03	0.06	−0.00	0.08
	(0.06)	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)
	[159,046]	[159,046]	[173,523]	[173,523]	[132,054]	[132,054]	[145,918]	[145,918]
Voucher school	0.02	−0.06	−0.02	−0.09	−0.02	−0.07	0.04	−0.08
	(0.06)	(0.05)	(0.05)	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)
	[159,046]	[159,046]	[173,523]	[173,523]	[132,054]	[132,054]	[145,918]	[145,918]
Private school	−0.02	−0.02	−0.03	−0.02	−0.03	0.00	−0.03	−0.02
	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
	[159,046]	[159,046]	[173,523]	[173,523]	[132,054]	[132,054]	[145,918]	[145,918]

Notes:

Table 4: Variation in main variables

	2003-2013 Cohorts				2000-2008 Cohorts			
	Women		Men		Women		Men	
	MP	FP	MP	FP	MP	FP	MP	FP
Raw Variation								
Mean	0.774	0.798	0.831	0.807	0.777	0.801	0.831	0.808
SD	0.134	0.130	0.121	0.131	0.133	0.128	0.119	0.129
Min	0.225	0.270	0.135	0.292	0.274	0.218	0.164	0.301
Max	0.997	0.999	0.998	0.996	0.997	0.999	0.997	0.996
Net of Program and Cohort Fixed Effects								
Mean	-0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	0.000
SD	0.026	0.032	0.024	0.030	0.025	0.031	0.023	0.028
Min	-0.371	-0.290	-0.395	-0.202	-0.280	-0.240	-0.366	-0.224
Max	0.293	0.219	0.349	0.210	0.287	0.269	0.285	0.436

Notes:

Table 5: Peer effects on graduation

	Women			Men		
	(1) Grad Univ	(2) Grad Univ on Time	(3) Grad Program	(4) Grad Univ	(5) Grad Univ on Time	(6) Grad Program
Panel A: All						
Mean rank of female peers	0.14^{***}	0.07	0.02	0.03	-0.00	0.03
	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)
Mean rank of male peers	-0.01	-0.07	-0.06	-0.02	-0.06	-0.07
	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)
N. Clus.	566	566	566	560	560	560
N. Obs.	161,007	161,007	161,007	176,140	176,140	176,140
Mean dependent variable	0.71	0.48	0.55	0.58	0.30	0.40
Panel B: STEM						
Mean rank of female peers	0.29^{**}	0.01	0.18	0.09	0.03	0.09
	(0.12)	(0.12)	(0.12)	(0.08)	(0.07)	(0.07)
Mean rank of male peers	-0.18	-0.35^{**}	-0.39^{**}	-0.11	-0.06	-0.15
	(0.18)	(0.16)	(0.16)	(0.11)	(0.10)	(0.12)
N. Clus.	163	163	163	163	163	163
N. Obs.	28,088	28,088	28,088	82,068	82,068	82,068
Mean dependent variable	0.64	0.29	0.32	0.55	0.23	0.29
Panel C: non-STEM						
Mean rank of female peers	0.10	0.10	-0.01	-0.06	-0.05	-0.06
	(0.06)	(0.07)	(0.08)	(0.07)	(0.07)	(0.08)
Mean rank of male peers	-0.01	-0.05	-0.05	0.01	-0.06	-0.05
	(0.05)	(0.06)	(0.06)	(0.07)	(0.07)	(0.08)
N. Clus.	403	403	403	397	397	397
N. Obs.	132,919	132,919	132,919	94,072	94,072	94,072
Mean dependent variable	0.73	0.52	0.60	0.61	0.37	0.49

Notes:

Table 6: Peer effects on graduation using alternative specification

	Women						Men					
	Grad Univ			Grad Program			Grad Univ			Grad Program		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: All												
Mean rank of female peers	0.12^{**}	0.10^{*}	0.08	−0.02	−0.02	−0.03	−0.04	−0.05	−0.03	−0.04	−0.04	−0.04
	(0.05)	(0.06)	(0.07)	(0.06)	(0.06)	(0.07)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)
Mean rank of male peers	−0.01	−0.02	−0.06	−0.07	−0.07	−0.08	0.01	0.01	0.07	−0.09	−0.10	−0.00
	(0.04)	(0.04)	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.08)	(0.07)	(0.07)	(0.08)
N. Clus.	566	566	566	566	566	566	559	559	558	559	559	558
N. Obs.	144,997	144,076	141,754	144,997	144,076	141,754	158,034	157,135	154,741	158,034	157,135	154,741
Mean dependent variable	0.7	0.7	0.7	0.6	0.6	0.6	0.6	0.6	0.6	0.4	0.4	0.4
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Program FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year x Program FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Program FE x $E(p_i\|\theta_i)$		✓			✓			✓			✓	
Program FE x $E(p_i\|\Theta_i)$			✓			✓			✓			✓
Panel B: STEM												
Mean rank of female peers	0.22^{*}	0.18	0.18	0.20	0.16	0.22	0.01	0.00	0.02	0.03	0.01	0.00
	(0.13)	(0.13)	(0.17)	(0.12)	(0.12)	(0.15)	(0.06)	(0.07)	(0.09)	(0.06)	(0.06)	(0.08)
Mean rank of male peers	−0.20	−0.22	−0.23	-0.31^{**}	-0.27^{*}	-0.31^{*}	−0.07	−0.06	0.07	-0.20^{*}	−0.20	−0.05
	(0.16)	(0.17)	(0.21)	(0.15)	(0.15)	(0.17)	(0.11)	(0.11)	(0.14)	(0.12)	(0.12)	(0.13)
N. Clus.	163	163	163	163	163	163	163	163	163	163	163	163
N. Obs.	25,338	25,227	25,017	25,338	25,227	25,017	73,967	73,652	73,054	73,967	73,652	73,054
Mean dependent variable	0.6	0.6	0.6	0.3	0.3	0.3	0.6	0.6	0.6	0.3	0.3	0.3
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Program FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year x Program FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Program FE x $E(p_i\|\theta_i)$		✓			✓			✓			✓	
Program FE x $E(p_i\|\Theta_i)$			✓			✓			✓			✓
Mean rank of female peers	0.09	0.08	0.06	−0.07	−0.06	−0.06	−0.11	−0.11	−0.08	−0.12	−0.10	−0.09
	(0.06)	(0.06)	(0.08)	(0.07)	(0.07)	(0.09)	(0.07)	(0.07)	(0.09)	(0.07)	(0.07)	(0.09)
Mean rank of male peers	−0.00	−0.01	−0.04	−0.06	−0.05	−0.06	0.04	0.04	0.08	−0.06	−0.07	0.01
	(0.04)	(0.04)	(0.06)	(0.06)	(0.06)	(0.07)	(0.08)	(0.08)	(0.10)	(0.08)	(0.08)	(0.10)
N. Clus.	403	403	403	403	403	403	396	396	395	396	396	395
N. Obs.	119,659	118,849	116,737	119,659	118,849	116,737	84,067	83,483	81,687	84,067	83,483	81,687
Mean dependent variable	0.7	0.7	0.7	0.6	0.6	0.6	0.6	0.6	0.6	0.5	0.5	0.5
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Program FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year x Program FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Program FE x $E(p_i\|\theta_i)$		✓			✓			✓			✓	
Program FE x $E(p_i\|\Theta_i)$			✓			✓			✓			✓

Notes:

Table 7: Peer effects on graduation using alternative measures of peer quality

	Women						Men					
	Grad Univ			Grad Program			Grad Univ			Grad Program		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: All												
Mean rank of peers	0.08			−0.07			0.01			−0.06		
	(0.07)			(0.08)			(0.06)			(0.07)		
% Female peers low performing		-0.03^{**}			−0.01			−0.01			−0.01	
		(0.01)			(0.01)			(0.01)			(0.01)	
% Male peers low performing		−0.01			−0.00			0.00			0.01	
		(0.01)			(0.02)			(0.02)			(0.02)	
% Female peers high performing			−0.00			−0.01			-0.02^{*}			−0.02
			(0.02)			(0.02)			(0.01)			(0.01)
% Male peers high performing			0.01			−0.01			0.01			−0.02
			(0.01)			(0.02)			(0.01)			(0.02)
Mean	0.72	0.71	0.71	0.56	0.55	0.55	0.58	0.58	0.58	0.40	0.40	0.40
N Clus	569	560	560	569	560	560	562	560	560	562	560	560
Obs	167,043	159,286	159,286	167,043	159,286	159,286	178,087	174,067	174,067	178,087	174,067	174,067
Panel A: STEM												
Mean rank of peers	0.18			−0.19			0.03			−0.02		
	(0.19)			(0.18)			(0.11)			(0.11)		
% Female peers low performing		−0.03			-0.05^{*}			−0.02			−0.02	
		(0.02)			(0.03)			(0.02)			(0.02)	
% Male peers low performing		−0.01			0.05			0.04			0.04	
		(0.04)			(0.04)			(0.03)			(0.03)	
% Female peers high performing			0.03			0.04			−0.01			0.00
			(0.03)			(0.03)			(0.02)			(0.02)
% Male peers high performing			−0.02			−0.05			−0.02			−0.03
			(0.04)			(0.03)			(0.03)			(0.03)
Mean	0.64	0.64	0.64	0.32	0.32	0.32	0.55	0.55	0.55	0.29	0.29	0.29
N Clus	163	163	163	163	163	163	163	163	163	163	163	163
Obs	28,088	28,088	28,088	28,088	28,088	28,088	83,070	80,077	80,077	83,070	80,077	80,077
Panel A: Non-STEM												
Mean rank of peers	0.04			−0.07			−0.05			-0.15^{*}		
	(0.08)			(0.09)			(0.07)			(0.09)		
% Female peers low performing		-0.02^{*}			0.00			−0.00			0.01	
		(0.01)			(0.02)			(0.02)			(0.02)	
% Male peers low performing		−0.00			−0.01			−0.01			−0.01	
		(0.02)			(0.02)			(0.02)			(0.02)	
% Female peers high performing			−0.01			−0.02			-0.05^{**}			-0.05^{**}
			(0.02)			(0.03)			(0.02)			(0.02)
% Male peers high performing			0.01			−0.01			0.02			−0.01
			(0.01)			(0.02)			(0.02)			(0.02)
Mean	0.73	0.73	0.73	0.61	0.60	0.60	0.61	0.61	0.61	0.50	0.49	0.49
N Clus	406	397	397	406	397	397	399	397	397	399	397	397
Obs	138,955	131,198	131,198	138,955	131,198	131,198	95,017	93,990	93,990	95,017	93,990	93,990

Notes:

Table 8: Earnings

	Women					Men				
	(1) Works at least 1 month	(2) Earnings	(3) Earnings | Works	(4) N of months of experience	(5) N of employers	(6) Works at least 1 month	(7) Earnings	(8) Earnings | Works	(9) N of months of experience	(10) N of employers
All										
Mean rank of female peers	0.08	1,736	620.8	0.79	0.11	−0.04	−397.2	−248.1	−3.60	−0.76
	(0.06)	(1,356)	(1,669)	(3.07)	(0.53)	(0.05)	(1,546)	(1,631)	(3.10)	(0.54)
Mean rank of male peers	−0.05	−1,896**	−1,437	−1.11	0.08	−0.02	−1,701	−1,454	−3.49	−0.62
	(0.05)	(954.1)	(1,148)	(2.32)	(0.44)	(0.07)	(1,531)	(1,723)	(3.59)	(0.63)
Mean dependent variable	0.58	8,918	15,365	24.22	4.37	0.62	10,595	17,055	25.49	4.70
N. Clus.	522	522	522	522	522	515	515	512	515	515
N. Obs.	131,411	131,411	76,274	131,411	131,411	145,240	145,240	90,227	145,240	145,240
STEM										
Mean rank of female peers	0.17	2,194	−179.4	3.60	0.42	−0.01	−682.8	−1,289	0.06	−0.34
	(0.14)	(3,910)	(4,949)	(6.34)	(1.06)	(0.07)	(2,238)	(2,171)	(4.17)	(0.72)
Mean rank of male peers	−0.07	−4,456	−6,434	−2.18	−1.00	−0.07	−4,790	−3,326	−3.54	−0.60
	(0.19)	(4,927)	(6,060)	(8.46)	(1.61)	(0.11)	(3,807)	(4,101)	(7.19)	(1.22)
Mean dependent variable	0.64	11,546	17,973	24.21	4.38	0.70	13,810	19,649	27.87	4.98
N. Clus.	133	133	133	133	133	133	133	133	133	133
N. Obs.	21,860	21,860	14,043	21,860	21,860	63,598	63,598	44,701	63,598	63,598
non-STEM										
Mean rank of female peers	0.06	1,789	1,006	0.73	0.20	−0.07	636.6	1,961	−8.09*	−1.29*
	(0.07)	(1,414)	(1,716)	(3.51)	(0.60)	(0.08)	(1,616)	(2,023)	(4.31)	(0.77)
Mean rank of male peers	−0.04	−1,543	−987.0	−0.83	0.17	0.00	−656.8	−1,029	−2.00	−0.38
	(0.05)	(953.6)	(1,138)	(2.43)	(0.46)	(0.08)	(1,502)	(1,683)	(4.29)	(0.76)
Mean dependent variable	0.57	8,394	14,777	24.22	4.36	0.56	8,091	14,508	23.63	4.49
N. Clus.	389	389	389	389	389	382	382	379	382	382
N. Obs.	109,551	109,551	62,231	109,551	109,551	81,642	81,642	45,526	81,642	81,642

Notes:

Table 9: Peer effects on the probability of working on alumni affiliated firms

	Women					Men				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Employed at firm with any					Employed at firm with any				
	Alumn	Female Alumn	Male Alumn	High Perf. Female Alumn	High Perf. Male Alumn	Alumn	Female Alumn	Male Alumn	High Perf. Female Alumn	High Perf. Male Alumn
All										
Mean rank of female peers	0.06	0.04	0.03	0.05	0.03	−0.01	0.04	−0.01	0.06*	0.03
	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.03)	(0.05)	(0.03)	(0.04)
Mean rank of male peers	0.01	0.00	0.01	0.05	0.02	−0.09	−0.05	−0.11**	−0.05	−0.09*
	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.06)	(0.05)	(0.05)	(0.04)	(0.05)
Mean dependent variable	0.27	0.23	0.18	0.18	0.15	0.26	0.16	0.22	0.12	0.19
N. Clus.	524	524	524	524	524	517	517	517	517	517
N. Obs.	131,700	131,700	131,700	131,700	131,700	145,426	145,426	145,426	145,426	145,426
STEM										
Mean rank of female peers	0.11	0.04	0.11	0.06	0.05	−0.07	0.00	−0.05	0.00	0.04
	(0.12)	(0.11)	(0.12)	(0.09)	(0.12)	(0.07)	(0.04)	(0.07)	(0.04)	(0.06)
Mean rank of male peers	0.10	0.02	0.04	0.06	0.02	−0.17	−0.06	−0.21*	−0.05	−0.22**
	(0.17)	(0.14)	(0.17)	(0.12)	(0.16)	(0.12)	(0.09)	(0.12)	(0.09)	(0.10)
Mean dependent variable	0.26	0.17	0.22	0.13	0.19	0.29	0.14	0.27	0.10	0.23
N. Clus.	133	133	133	133	133	133	133	133	133	133
N. Obs.	21,860	21,860	21,860	21,860	21,860	63,598	63,598	63,598	63,598	63,598
non-STEM										
Mean rank of female peers	0.04	0.03	0.01	0.04	0.01	0.07	0.09*	0.06	0.13**	0.04
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)
Mean rank of male peers	0.00	0.00	0.01	0.05	0.02	−0.09	−0.05	−0.09*	−0.06	−0.06
	(0.05)	(0.04)	(0.03)	(0.04)	(0.03)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)
Mean dependent variable	0.27	0.24	0.17	0.20	0.14	0.23	0.18	0.18	0.14	0.15
N. Clus.	391	391	391	391	391	384	384	384	384	384
N. Obs.	109,840	109,840	109,840	109,840	109,840	81,828	81,828	81,828	81,828	81,828

Notes:

Table 10: Peer effects on Fertility

	Women		Men	
	(1)	(2)	(3)	(4)
	Child Born	N of Children	Child Born	N of Children
All				
Mean rank of female peers	0.027	−0.039	0.062*	0.018
	(0.04)	(0.07)	(0.03)	(0.05)
Mean rank of male peers	0.002	−0.024	0.009	−0.021
	(0.03)	(0.06)	(0.04)	(0.06)
Mean dependent variable	0.17	0.27	0.13	0.21
N. Clus.	506	506	499	499
N. Obs.	156,761	156,761	171,687	171,687
STEM				
Mean rank of female peers	−0.163	−0.347**	0.067	−0.020
	(0.11)	(0.16)	(0.05)	(0.08)
Mean rank of male peers	0.226*	0.408**	−0.009	0.033
	(0.13)	(0.19)	(0.08)	(0.12)
Mean dependent variable	0.15	0.26	0.13	0.22
N. Clus.	130	130	130	130
N. Obs.	25,014	25,014	75,158	75,158
non-STEM				
Mean rank of female peers	0.072	0.023	0.065	0.062
	(0.05)	(0.08)	(0.05)	(0.07)
Mean rank of male peers	−0.010	−0.053	0.032	−0.020
	(0.03)	(0.06)	(0.05)	(0.08)
Mean dependent variable	0.17	0.28	0.13	0.21
N. Clus.	376	376	369	369
N. Obs.	131,747	131,747	96,529	96,529

Notes:

Table 11: Peer effects on Marriage

	Women							Men						
	(1) Married	(2) Has Spouse	(3) Spouse from program	(4) Spouse GPA rank	(5) Spouse Lang rank	(6) Spouse Math rank	(7) Spouse annual earnings	(8) Married	(9) Has Spouse	(10) Spouse from program	(11) Spouse GPA rank	(12) Spouse Lang rank	(13) Spouse Math rank	(14) Spouse annual earnings
All														
Mean rank of female peers	−0.044	−0.017	−0.016	−0.003	0.017	0.101	8,461***	−0.028	0.019	0.026*	0.080	0.057	0.120**	3,850
	(0.05)	(0.05)	(0.02)	(0.07)	(0.07)	(0.07)	(2,755)	(0.04)	(0.05)	(0.01)	(0.05)	(0.05)	(0.05)	(2,364)
Mean rank of male peers	−0.021	−0.052	−0.013	−0.024	0.048	0.040	−1,187	−0.010	−0.010	−0.064***	−0.059	−0.022	−0.055	123.4
	(0.05)	(0.04)	(0.01)	(0.06)	(0.06)	(0.05)	(1,961)	(0.04)	(0.06)	(0.02)	(0.07)	(0.06)	(0.06)	(2,761)
Mean dependent variable	0.26	0.41	0.04	0.57	0.63	0.67	18,964.23	0.20	0.33	0.03	0.64	0.62	0.59	12,742.93
N. Clus.	523	523	523	521	521	521	523	516	516	516	508	508	508	509
N. Obs.	131,990	131,990	131,990	32,028	32,072	32,047	54,645	145,559	145,559	145,559	36,003	35,821	35,781	47,925
STEM														
Mean rank of female peers	0.057	−0.027	0.021	0.021	0.021	0.292*	10,510	−0.014	0.039	0.026*	0.123*	0.094	0.170***	3,781
	(0.12)	(0.14)	(0.06)	(0.17)	(0.17)	(0.17)	(7,211)	(0.06)	(0.07)	(0.01)	(0.06)	(0.07)	(0.06)	(3,581)
Mean rank of male peers	−0.142	−0.089	0.048	0.109	0.014	−0.027	3,755	0.032	0.052	0.004	0.126	0.123	0.155	838.6
	(0.14)	(0.20)	(0.06)	(0.23)	(0.20)	(0.25)	(9,276)	(0.10)	(0.12)	(0.03)	(0.12)	(0.12)	(0.11)	(5,447)
Mean dependent variable	0.25	0.39	0.05	0.60	0.64	0.71	21,414.86	0.20	0.34	0.02	0.63	0.59	0.59	12,345.07
N. Clus.	135	135	135	133	133	133	135	135	135	135	135	135	135	135
N. Obs.	21,117	21,117	21,117	4,892	4,890	4,888	8,227	62,807	62,807	62,807	15,945	15,865	15,850	21,305
non-STEM														
Mean rank of female peers	−0.067	−0.006	−0.029	−0.017	0.025	0.065	7,162**	−0.052	−0.015	0.016	−0.005	−0.014	0.019	4,947
	(0.06)	(0.06)	(0.02)	(0.08)	(0.08)	(0.08)	(3,023)	(0.05)	(0.07)	(0.03)	(0.08)	(0.08)	(0.08)	(3,300)
Mean rank of male peers	−0.010	−0.045	−0.016	−0.035	0.047	0.042	−1,875	−0.021	−0.017	−0.087***	−0.117	−0.078	−0.142*	350.2
	(0.05)	(0.04)	(0.01)	(0.06)	(0.06)	(0.05)	(2,021)	(0.05)	(0.07)	(0.03)	(0.08)	(0.07)	(0.07)	(3,175)
Mean dependent variable	0.26	0.42	0.03	0.57	0.63	0.67	18,529.89	0.19	0.32	0.05	0.65	0.63	0.60	13,061.35
N. Clus.	388	388	388	388	388	388	388	381	381	381	373	373	373	374
N. Obs.	110,873	110,873	110,873	27,136	27,182	27,159	46,418	82,752	82,752	82,752	20,058	19,956	19,931	26,620

Notes:

Table 12: Heterogeneous results by program characteristics

	Women				Men			
	Grad Univ	Grad Program	Earnings	Has a Child	Grad Univ	Grad Program	Earnings	Has a Child
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Male vs Female-Dominated Program								
Male dominated program ($>$ 60% Men)								
Mean rank of female peers	0.23^{**}	0.18	$7,828^{**}$	-0.09	0.04	0.08	$-1,378$	-0.10
	(0.12)	(0.12)	(3,661)	(0.12)	(0.07)	(0.07)	(2,065)	(0.07)
Mean rank of male peers	-0.03	0.03	$-3,004$	-0.19	-0.05	-0.05	$-3,756$	0.04
	(0.17)	(0.16)	(5,891)	(0.19)	(0.11)	(0.12)	(3,611)	(0.09)
Mean	0.7	0.4	11,950	0.3	0.6	0.3	13,585	0.2
N. Clus	156	156	132	132	156	156	132	132
N. Obs	23,741	23,741	19,075	19,075	82,336	82,336	65,595	65,595
Female dominated program ($>$ 60% Women)								
Mean rank of female peers	0.08	0.04	526.1	-0.06	-0.06	-0.16	$-1,852$	-0.15
	(0.09)	(0.12)	(1,819)	(0.10)	(0.15)	(0.17)	(3,197)	(0.14)
Mean rank of male peers	-0.05	-0.08	$-1,312$	0.03	-0.14	-0.22^{*}	-833.7	0.12
	(0.06)	(0.07)	(1,094)	(0.05)	(0.12)	(0.12)	(1,966)	(0.09)
Mean	0.8	0.7	8,688	0.3	0.6	0.5	7,808	0.2
N. Clus	178	178	168	168	172	172	161	161
N. Obs	64,045	64,045	51,078	51,078	21,200	21,200	17,360	17,360
Panel A: Selective vs Non-Selective Program								
Selective program								
Mean rank of female peers	0.15	0.03	$7,097^{**}$	-0.18^{*}	0.09	0.09	2,861	-0.05
	(0.10)	(0.11)	(3,430)	(0.10)	(0.07)	(0.07)	(2,389)	(0.07)
Mean rank of male peers	0.17^{*}	0.09	$-2,001$	-0.09	-0.05	-0.09	$-1,838$	-0.11
	(0.09)	(0.14)	(2,946)	(0.10)	(0.11)	(0.13)	(3,411)	(0.09)
Mean	0.8	0.6	10,153	0.2	0.6	0.4	12,006	0.2
N. Clus	269	269	245	245	269	269	245	245
N. Obs	85,425	85,425	69,285	69,285	111,495	111,495	90,411	90,411
Non-selective program								
Mean rank of female peers	0.13^{**}	0.02	-913.5	-0.02	-0.02	-0.03	$-4,394^{**}$	-0.05
	(0.07)	(0.08)	(1,329)	(0.07)	(0.08)	(0.08)	(1,760)	(0.07)
Mean rank of male peers	-0.05	-0.09	$-2,200^{**}$	0.01	-0.02	-0.08	$-2,416$	0.01
	(0.06)	(0.07)	(983.2)	(0.05)	(0.07)	(0.07)	(1,576)	(0.07)
Mean	0.7	0.5	7,558	0.4	0.5	0.4	8,290	0.3
N. Clus	297	297	279	279	291	291	272	272
N. Obs	75,582	75,582	62,415	62,415	64,645	64,645	55,015	55,015
Panel C: High vs low dropout rates in Program								
High Dropout rates								
Mean rank of female peers	0.22^{**}	0.01	$4,398^{**}$	-0.12	0.02	0.04	1,167	-0.01
	(0.09)	(0.08)	(2,154)	(0.09)	(0.06)	(0.05)	(1,782)	(0.06)
Mean rank of male peers	-0.01	-0.05	$-1,162$	-0.12	0.01	-0.05	$-2,014$	-0.09
	(0.11)	(0.10)	(2,117)	(0.10)	(0.08)	(0.09)	(2,319)	(0.08)
Mean	0.6	0.3	7,967	0.3	0.5	0.2	10,790	0.2
N. Clus	222	222	228	228	222	222	228	228
N. Obs	45,974	45,974	44,828	44,828	83,605	83,605	76,078	76,078
Low Dropout rates								
Mean rank of female peers	0.10	0.05	449.0	-0.03	0.05	0.01	$-2,865$	-0.14^{*}
	(0.07)	(0.09)	(1,702)	(0.08)	(0.10)	(0.11)	(2,506)	(0.08)
Mean rank of male peers	-0.01	-0.06	$-2,003^{*}$	0.03	-0.03	-0.08	-461.9	0.03
	(0.06)	(0.07)	(1,073)	(0.05)	(0.09)	(0.10)	(2,008)	(0.08)
Mean	0.8	0.7	9,416	0.3	0.7	0.6	10,392	0.2
N. Clus	344	344	296	296	338	338	289	289
N. Obs	115,033	115,033	86,872	86,872	92,535	92,535	69,348	69,348

Notes:

Appendix

February 22, 2021

A Data Construction

Earnings records were obtained from the unemployment insurance records of Chile's Ministry of Labor for the period between 2002 and 2017. This data had to be accessed on-site at the Ministry of Labor. To add educational records we digitized hard copies of published test score results stored in a local newspaper (El Mercurio) for all students taking the standardized admission test in the 1999 to 2007 period. Although DEMRE has data on educational records for students who took the test as of 1999, we were unable to have both agencies work together to match the data. Instead, we turned to publicly available educational records stored in el *El Mercurio* to gather information on students' unique national identification numbers (NIDs) and test score results. This data was then matched with earnings records, fertility records and other educational information at the Ministry of Labor. Of the total number of individuals who were in the margin of admission to TE and HASS between 1999 and 2007, 97% were matched to national identification numbers and could be matched with earnings and fertility records. This is the sample we use in our study.

B Employment Sector by Field and Gender in Chile

Table B.1 uses data from Casen 2017, a survey representative of the Chilean population, to categorize the percentage of individuals aged 30 to 38 years old who graduated from each field of study that are unemployed, employed in the private sector, public sector, or self-employed. Our earnings records prevent us from seeing the self-employed and public sector employees, which represent approximately 15% and 20% of individuals in our sample.

Table B.1: Employment by Field of Graduation

			Employment			
		Obs	Unemployed	Employed Private Sector	Employed Public Sector	Self Employed
			(1)	(2)	(3)	(4)
Field						
All	Male	1,592	0.101	0.528	0.203	0.168
	Female	1,880	0.141	0.456	0.300	0.103
STEM	Male	563	0.080	0.667	0.122	0.130
	Female	210	0.133	0.651	0.106	0.110
Non-STEM	Male	1,029	0.112	0.449	0.250	0.189
	Female	1,670	0.142	0.429	0.327	0.102

Notes: This table shows data from a nationally representative survey (CASEN 2017) on the fraction of men and women graduating from each field category who were unemployed (column 1), employed in the private or public sectors (columns 2 & 3), or self-employed (column 4).

C Robustness Checks

Table C.1: Balance Test STEM programs

	2003-2013 Cohorts				2000-2008 Cohorts			
	Women		Men		Women		Men	
Variable	Mean rank of female peers (1)	Mean rank of male peers (2)	Mean rank of female peers (3)	Mean rank of male peers (4)	Mean rank of female peers (5)	Mean rank of male peers (6)	Mean rank of female peers (7)	Mean rank of male peers (8)
Mother primary ed	−0.02	−0.13	0.05	0.12*	−0.05	−0.09	−0.02	0.03
	(0.09)	(0.11)	(0.04)	(0.07)	(0.09)	(0.13)	(0.06)	(0.08)
	[25,717]	[25,717]	[74,341]	[74,341]	[21,904]	[21,904]	[63,165]	[63,165]
Mother secondary ed	−0.18*	0.25	−0.01	0.11	−0.07	−0.02	−0.07	0.20
	(0.11)	(0.17)	(0.06)	(0.11)	(0.14)	(0.21)	(0.06)	(0.12)
	[25,717]	[25,717]	[74,341]	[74,341]	[21,904]	[21,904]	[63,165]	[63,165]
Mother tertiary ed	0.20*	−0.04	−0.05	−0.18	0.17	0.16	0.08	−0.21*
	(0.11)	(0.14)	(0.05)	(0.11)	(0.13)	(0.17)	(0.06)	(0.12)
	[25,717]	[25,717]	[74,341]	[74,341]	[21,904]	[21,904]	[63,165]	[63,165]
Father primary ed	0.04	−0.14	0.07**	−0.03	−0.08	0.19	−0.00	−0.03
	(0.09)	(0.11)	(0.04)	(0.08)	(0.10)	(0.13)	(0.04)	(0.08)
	[25,717]	[25,717]	[74,341]	[74,341]	[21,904]	[21,904]	[63,165]	[63,165]
Father secondary ed	−0.07	0.16	−0.02	0.20*	0.04	0.02	−0.02	0.01
	(0.13)	(0.17)	(0.06)	(0.12)	(0.14)	(0.20)	(0.07)	(0.14)
	[24,464]	[24,464]	[71,694]	[71,694]	[20,729]	[20,729]	[60,589]	[60,589]
Father tertiary ed	−0.00	0.05	−0.04	−0.09	0.02	−0.22	0.04	−0.08
	(0.13)	(0.15)	(0.05)	(0.11)	(0.15)	(0.20)	(0.07)	(0.13)
	[24,464]	[24,464]	[71,694]	[71,694]	[20,729]	[20,729]	[60,589]	[60,589]
Mother works	0.15	0.27	−0.05	0.03	0.16	−0.15	−0.01	0.01
	(0.11)	(0.18)	(0.06)	(0.11)	(0.13)	(0.18)	(0.07)	(0.13)
	[25,643]	[25,643]	[74,144]	[74,144]	[21,853]	[21,853]	[62,972]	[62,972]
Father works	0.11	−0.12	−0.05	0.10	0.14	−0.22	0.06	−0.09
	(0.09)	(0.11)	(0.05)	(0.09)	(0.12)	(0.13)	(0.05)	(0.10)
	[23,831]	[23,831]	[70,242]	[70,242]	[20,314]	[20,314]	[59,550]	[59,550]
Mother works fulltime	0.25**	0.10	−0.06	−0.00	0.15	−0.21	0.02	−0.04
	(0.11)	(0.15)	(0.06)	(0.11)	(0.13)	(0.16)	(0.07)	(0.14)
	[25,643]	[25,643]	[74,144]	[74,144]	[21,853]	[21,853]	[62,972]	[62,972]
Father works fulltime	−0.01	−0.06	−0.11*	0.10	0.11	−0.18	0.01	−0.18
	(0.14)	(0.14)	(0.06)	(0.12)	(0.15)	(0.17)	(0.08)	(0.13)
	[23,831]	[23,831]	[70,242]	[70,242]	[20,314]	[20,314]	[59,550]	[59,550]
Public school	0.26**	0.05	0.08	0.15	0.13	0.07	−0.02	0.14
	(0.12)	(0.16)	(0.07)	(0.12)	(0.16)	(0.19)	(0.06)	(0.12)
	[26,900]	[26,900]	[78,170]	[78,170]	[22,118]	[22,118]	[64,208]	[64,208]
Voucher school	−0.27**	−0.02	−0.10	−0.09	−0.10	−0.09	0.08	−0.04
	(0.12)	(0.17)	(0.07)	(0.12)	(0.16)	(0.17)	(0.08)	(0.13)
	[26,900]	[26,900]	[78,170]	[78,170]	[22,118]	[22,118]	[64,208]	[64,208]
Private school	0.01	0.00	0.01	−0.11	−0.05	−0.04	−0.04	−0.10
	(0.06)	(0.08)	(0.03)	(0.07)	(0.10)	(0.10)	(0.05)	(0.09)
	[26,900]	[26,900]	[78,170]	[78,170]	[22,118]	[22,118]	[64,208]	[64,208]

Notes:

Table C.2: Balance Test non-STEM programs

	2003-2013 Cohorts				2000-2008 Cohorts			
	Women		Men		Women		Men	
Variable	Mean rank of female peers (1)	Mean rank of male peers (2)	Mean rank of female peers (3)	Mean rank of male peers (4)	Mean rank of female peers (5)	Mean rank of male peers (6)	Mean rank of female peers (7)	Mean rank of male peers (8)
Mother primary ed	−0.02	−0.01	0.02	0.06	−0.06	0.02	0.05	0.04
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
	[126,190]	[126,190]	[88,565]	[88,565]	[108,788]	[108,788]	[80,735]	[80,735]
Mother secondary ed	−0.05	0.06	0.02	−0.06	0.08	0.06	0.02	−0.02
	(0.06)	(0.04)	(0.07)	(0.07)	(0.06)	(0.05)	(0.08)	(0.07)
	[126,190]	[126,190]	[88,565]	[88,565]	[108,788]	[108,788]	[80,735]	[80,735]
Mother tertiary ed	0.03	−0.03	−0.06	0.01	−0.04	-0.09^{**}	−0.08	−0.02
	(0.05)	(0.04)	(0.06)	(0.06)	(0.06)	(0.04)	(0.07)	(0.07)
	[126,190]	[126,190]	[88,565]	[88,565]	[108,788]	[108,788]	[80,735]	[80,735]
Father primary ed	−0.04	-0.06^{*}	0.03	0.04	−0.02	−0.02	0.07	0.05
	(0.04)	(0.03)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)
	[126,190]	[126,190]	[88,565]	[88,565]	[108,788]	[108,788]	[80,735]	[80,735]
Father secondary ed	−0.06	0.09^{*}	−0.05	−0.04	−0.04	0.09^{*}	0.00	−0.04
	(0.06)	(0.05)	(0.08)	(0.07)	(0.07)	(0.05)	(0.08)	(0.07)
	[120,417]	[120,417]	[85,277]	[85,277]	[102,974]	[102,974]	[76,960]	[76,960]
Father tertiary ed	0.06	−0.01	−0.02	0.00	0.04	−0.08	−0.10	−0.06
	(0.06)	(0.05)	(0.07)	(0.06)	(0.07)	(0.06)	(0.08)	(0.07)
	[120,417]	[120,417]	[85,277]	[85,277]	[102,974]	[102,974]	[76,960]	[76,960]
Mother works	0.04	0.02	−0.10	−0.05	−0.10	0.02	−0.10	0.00
	(0.06)	(0.05)	(0.07)	(0.07)	(0.07)	(0.05)	(0.07)	(0.08)
	[125,798]	[125,798]	[88,306]	[88,306]	[108,314]	[108,314]	[80,434]	[80,434]
Father works	−0.02	0.04	−0.02	0.09^{*}	0.04	0.01	−0.05	0.02
	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.03)	(0.06)	(0.06)
	[117,491]	[117,491]	[83,539]	[83,539]	[100,721]	[100,721]	[75,561]	[75,561]
Mother works fulltime	−0.01	0.01	-0.12^{*}	−0.00	-0.10^{*}	0.02	−0.05	−0.03
	(0.06)	(0.05)	(0.07)	(0.07)	(0.06)	(0.05)	(0.08)	(0.07)
	[125,798]	[125,798]	[88,306]	[88,306]	[108,314]	[108,314]	[80,434]	[80,434]
Father works fulltime	0.06	0.02	−0.05	0.05	−0.01	0.02	−0.05	−0.02
	(0.06)	(0.05)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)
	[117,491]	[117,491]	[83,539]	[83,539]	[100,721]	[100,721]	[75,561]	[75,561]
Public school	−0.02	0.03	−0.02	0.12^{*}	0.02	0.07	0.02	0.07
	(0.06)	(0.05)	(0.06)	(0.06)	(0.07)	(0.05)	(0.07)	(0.08)
	[131,029]	[131,029]	[92,216]	[92,216]	[109,826]	[109,826]	[81,955]	[81,955]
Voucher school	0.04	−0.01	0.10	-0.12^{*}	−0.01	−0.07	−0.01	−0.10
	(0.07)	(0.05)	(0.07)	(0.07)	(0.07)	(0.06)	(0.08)	(0.07)
	[131,029]	[131,029]	[92,216]	[92,216]	[109,826]	[109,826]	[81,955]	[81,955]
Private school	0.01	−0.03	-0.10^{**}	−0.01	−0.03	−0.01	−0.02	−0.01
	(0.03)	(0.02)	(0.04)	(0.04)	(0.04)	(0.03)	(0.06)	(0.05)
	[131,029]	[131,029]	[92,216]	[92,216]	[109,826]	[109,826]	[81,955]	[81,955]

Notes:

Table C.3: Variation in main variables for STEM and non-STEM programs

	2004-2012 Cohorts				2000-2008 Cohorts			
	Women		Men		Women		Men	
	MP	FP	MP	FP	MP	FP	MP	FP
Panel A: All								
Mean	0.000	-0.000	0.000	0.000	-0.000	-0.000	0.000	-0.000
SD	0.025	0.030	0.022	0.028	0.025	0.031	0.023	0.028
Min	-0.358	-0.276	-0.406	-0.191	-0.277	-0.240	-0.366	-0.223
Max	0.269	0.217	0.333	0.208	0.294	0.269	0.285	0.451
Panel B: STEM								
Mean	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
SD	0.026	0.019	0.017	0.031	0.026	0.020	0.018	0.031
Min	-0.359	-0.096	-0.158	-0.194	-0.279	-0.120	-0.143	-0.200
Max	0.272	0.090	0.136	0.205	0.266	0.097	0.130	0.450
Panel C: non-STEM								
Mean	-0.000	-0.000	-0.000	-0.000	0.000	0.000	-0.000	0.000
SD	0.024	0.032	0.026	0.026	0.025	0.032	0.026	0.025
Min	-0.217	-0.276	-0.408	-0.159	-0.272	-0.239	-0.364	-0.220
Max	0.243	0.218	0.336	0.149	0.294	0.271	0.284	0.211

Notes:

Table C.4: Correlation between weights attached to two-way fixed effects regressions and program characteristics

	Women		Men	
	Mean rank of female peers	Mean rank of male peers	Mean rank of female peers	Mean rank of male peers
Program characteristics				
% Enrolled in program that are male	.0032499	-.0248612	.00989336	-.01475799
Program size	-.01399893	-.01725399	-.01732504	-.01378081
Math focused	-.00755493	-.01864873	-.00691296	-.01601178
Program dropout rate	.010834	-.00196849	.00998083	.00035997

Notes:

Table C.5: Estimates for women using alternative specifications

	Grad Univ			Grad Program			Work at least 1 month			Earnings		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: All												
Mean rank of female peers	0.20^{***}	0.13^{**}	0.14^{***}	0.17^{***}	0.09	0.10	-0.03	0.05	0.09	-640.5	1,010	1,437
	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(1,535)	(1,390)	(1,387)
Mean rank of male peers	-0.04	-0.05	-0.05	-0.08	-0.09	-0.08	-0.07^{*}	-0.06	-0.07	$-2,492^{***}$	$-2,199^{**}$	$-2,232^{**}$
	(0.04)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.04)	(0.05)	(0.05)	(919.8)	(960.7)	(963.9)
N. Clus.	486	486	486	486	486	486	465	465	465	465	465	465
N. Obs.	133,371	133,371	133,204	133,371	133,371	133,204	102,738	102,738	102,647	99,914	99,914	99,831
Mean dependent variable	0.8	0.8	0.8	0.6	0.6	0.6	0.6	0.6	0.6	8,054.4	8,054.4	8,054.4
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Program FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year x Program FE		✓	✓		✓	✓		✓	✓		✓	✓
Covars			✓			✓			✓			✓
Panel B: STEM												
Mean rank of female peers	0.24^{**}	0.22^{*}	0.22^{*}	0.28^{**}	0.28^{**}	0.26^{*}	0.13	0.23	0.27^{*}	3,199	3,211	3,975
	(0.11)	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)	(0.14)	(0.15)	(0.15)	(3,695)	(4,043)	(4,067)
Mean rank of male peers	-0.17	-0.25^{*}	-0.22	-0.60^{***}	-0.52^{***}	-0.51^{***}	-0.28^{*}	-0.31	-0.29	$-11,070^{**}$	$-12,020^{**}$	$-11,950^{**}$
	(0.15)	(0.15)	(0.15)	(0.17)	(0.18)	(0.17)	(0.16)	(0.19)	(0.19)	(4,491)	(4,930)	(5,194)
N. Clus.	138	138	138	138	138	138	114	114	114	114	114	114
N. Obs.	20,146	20,146	20,141	20,146	20,146	20,141	14,058	14,058	14,053	13,675	13,675	13,670
Mean dependent variable	0.7	0.7	0.7	0.4	0.4	0.4	0.6	0.6	0.6	10,457.8	10,457.8	10,456.9
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Program FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year x Program FE		✓	✓		✓	✓		✓	✓		✓	✓
Covars			✓			✓			✓			✓
Panel C: non-STEM												
Mean rank of female peers	0.18^{***}	0.09	0.11^{*}	0.15^{**}	0.05	0.07	-0.05	0.03	0.05	$-1,132$	875.3	1,272
	(0.06)	(0.06)	(0.06)	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(1,688)	(1,430)	(1,416)
Mean rank of male peers	-0.03	-0.04	-0.04	-0.05	-0.06	-0.06	-0.05	-0.04	-0.04	$-1,772^{**}$	$-1,447$	$-1,461$
	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(902.7)	(947.4)	(947.9)
N. Clus.	348	348	348	348	348	348	351	351	351	351	351	351
N. Obs.	113,225	113,225	113,063	113,225	113,225	113,063	88,680	88,680	88,594	86,239	86,239	86,161
Mean dependent variable	0.8	0.8	0.8	0.6	0.6	0.6	0.6	0.6	0.6	7,673.3	7,673.3	7,673.2
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Program FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year x Program FE		✓	✓		✓	✓		✓	✓		✓	✓
Covars			✓			✓			✓			✓

Notes:

Table C.6: Estimates for men using alternative specifications

	Grad Univ			Grad Program			Work at least 1 month			Earnings		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: All												
Mean rank of female peers	0.03	0.04	0.04	0.03	0.05	0.05	−0.08	−0.07	−0.04	−639.8	−651.0	771.0
	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)	(1,530)	(1,663)	(1,558)
Mean rank of male peers	−0.04	−0.03	−0.02	−0.09	−0.06	−0.06	−0.04	−0.00	−0.01	−2,205	−2,102	−2,603
	(0.05)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(1,605)	(1,615)	(1,615)
N. Clus.	481	481	481	481	481	481	458	458	458	458	458	458
N. Obs.	133,189	133,189	133,164	133,189	133,189	133,164	100,946	100,946	100,785	98,053	98,053	97,896
Mean dependent variable	0.6	0.6	0.6	0.4	0.4	0.4	0.6	0.6	0.6	9,162.4	9,162.4	9,154.1
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Program FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year x Program FE		✓	✓		✓	✓		✓	✓		✓	✓
Covars			✓			✓			✓			✓
Panel B: STEM												
Mean rank of female peers	0.02	0.07	0.07	0.03	0.09	0.09	−0.05	−0.06	−0.01	−742.5	−916.8	1,263
	(0.06)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.07)	(2,355)	(2,451)	(2,152)
Mean rank of male peers	−0.04	0.01	0.00	−0.27**	−0.08	−0.09	−0.08	−0.04	−0.07	−6,080	−5,858	−7,868*
	(0.10)	(0.11)	(0.11)	(0.14)	(0.14)	(0.15)	(0.10)	(0.11)	(0.11)	(3,963)	(4,208)	(4,075)
N. Clus.	138	138	138	138	138	138	114	114	114	114	114	114
N. Obs.	58,188	58,188	58,188	58,188	58,188	58,188	39,355	39,355	39,215	38,175	38,175	38,038
Mean dependent variable	0.6	0.6	0.6	0.3	0.3	0.3	0.7	0.7	0.7	12,369.7	12,369.7	12,356.8
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Program FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year x Program FE		✓	✓		✓	✓		✓	✓		✓	✓
Covars			✓			✓			✓			✓
Panel C: non-STEM												
Mean rank of female peers	0.03	−0.01	−0.02	0.01	−0.03	−0.04	−0.11	−0.08	−0.08	−373.0	181.1	358.2
	(0.06)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)	(1,740)	(1,640)	(1,648)
Mean rank of male peers	−0.04	−0.05	−0.04	−0.04	−0.08	−0.08	0.00	0.01	0.01	−628.1	−1,083	−958.8
	(0.06)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)	(0.09)	(0.09)	(1,478)	(1,520)	(1,534)
N. Clus.	343	343	343	343	343	343	344	344	344	344	344	344
N. Obs.	75,001	75,001	74,976	75,001	75,001	74,976	61,591	61,591	61,570	59,878	59,878	59,858
Mean dependent variable	0.7	0.7	0.7	0.5	0.5	0.5	0.5	0.5	0.6	7,117.6	7,117.6	7,118.9
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Program FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year x Program FE		✓	✓		✓	✓		✓	✓		✓	✓
Covars			✓			✓			✓			✓

Notes: