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College peer effects, gender, and STEM☆

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ABSTRACT

Women remain significantly underrepresented in Science, Technology, Engineering, and Mathematics (STEM) fields. We examine whether the ability of male and female college peers contributes to this gap. Using administrative data from Chile covering 33 universities and over 100 college majors, we exploit variation in peer composition across cohorts within programs (college major-university combinations) to identify causal effects. We track long-term outcomes including graduation, labor market performance, fertility, and marriage. Our results reveal substantial peer ability effects specific to women in STEM. Higher-ability female peers increase women's probability of graduating from STEM programs, while higher-ability male peers decrease it. In the longer run, higher-ability male peers also reduce women's employment, earnings, and work experience, while higher-ability female peers reduce fertility. We find no comparable effects for women in non-STEM fields or for men. These findings reveal that the ability of male versus female peers plays a critical role in shaping women's outcomes specifically in STEM environments.

1. Introduction

Women remain underrepresented in Science, Technology, Engineering, and Mathematics (STEM) fields across most developed and developing countries. In the United States, women account for about 39% of bachelor's degrees granted in STEM fields overall, but this aggregate figure masks substantial variation across disciplines: women represent 66% of degrees in biological sciences but only 23% in computer science and 25% in engineering.[1] The pattern is even more stark in Chile, the focus of our study, where women represented only 27% of STEM graduates in 2024. This sex gap has important implications: STEM careers are associated with higher earnings,[2] meaning women may be missing significant economic opportunities, while STEM fields miss out on women's potential contributions (Hsieh et al., 2019). Despite numerous public and private initiatives to encourage women's participation in STEM, progress has been limited. Understanding what factors contribute to women's underrepresentation is therefore crucial for designing more effective policies.

A natural candidate for explaining why women leave STEM is the peer environment they face in college. A large literature on college peer effects shows that peers influence academic achievement and educational choices (Carrell et al., 2009; De Giorgi et al., 2010; Jain & Kapoor, 2015; Sacerdote, 2001; Zimmerman, 2003).[3] Within the context of STEM, most existing work has examined how peer sex composition — specifically, the share of female peers — affects women's

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[1] National Center for Education Statistics (NCES), Digest of Education Statistics, Table 318.30 (bachelor's degrees, 2021–22). STEM includes biological sciences, mathematics and statistics, physical sciences, computer sciences, and engineering.

[2] A number of papers have documented that differences in men and women's choices of college major (Sloane et al., 2021), occupation, and industry (Altonji & Blank, 1999; Blau et al., 2009; Blau & Kahn, 2017; Groshen, 1991; Macpherson & Hirsch, 1995) explain a significant part of the sex wage gap in an accounting sense.

[3] For reviews, see Epple and Romano (2011) and Sacerdote (2011).

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outcomes (Bostwick & Weinberg, 2022).[4] Less is known about whether other peer characteristics, such as the academic ability of male versus female peers, also affect women's persistence and success in STEM in college. Understanding this is particularly policy-relevant because universities may be able to shape the peer environment students experience within their programs.

In this paper, we examine how the ability of male and female peers affects men's and women's long-term outcomes, including graduation, earnings, fertility, and marriage, both in STEM and non-STEM fields. Focusing on peer ability of male and female students is motivated by evidence suggesting that the sex of high-ability peers may matter for students' outcomes (Cools et al., 2022; Mouganie & Wang, 2020 document this in high school, though there is less evidence for college settings). Sex differences could emerge through several channels. Social interactions are stronger among same-sex peers (Marmaros & Sacerdote, 2006), potentially amplifying learning spillovers and role-model effects from same-sex high-ability peers. Conversely, exposure to high-ability opposite-sex peers could reinforce gender stereotypes or create competitive dynamics.[5] These mechanisms may be particularly important in STEM environments, where women are underrepresented and stereotype threat is more salient (Spencer et al., 1999; Steele & Aronson, 1995; Steele et al., 2002). Examining both STEM and non-STEM fields allows us to test whether peer gender dynamics are specific to these minority settings or reflect more general patterns across disciplines.

To answer these questions, we use administrative data from Chile covering 33 universities and over 100 college majors. In the Chilean higher education system, students apply and enroll directly into university-major combinations (which we refer to as "programs"), creating well-defined peer groups that share highly structured curricula throughout their academic careers. We exploit variation in peer composition across cohorts within programs to identify causal effects. Our setting offers several advantages: we observe students' academic ability at the time of college admission through standardized math test scores, which are determined before program entry and therefore not affected by peer composition, and we track long-term outcomes including graduation, labor market performance, fertility, and marriage using comprehensive administrative data.

Our results indicate that peer ability can significantly affect women's persistence in STEM and their long-term outcomes. Women in STEM benefit from higher-ability female peers but are harmed by higher-ability male peers. A one standard deviation increase in female peer ability increases the probability of graduating from a STEM program by 1.3%, while a one standard deviation increase in male peer ability decreases this probability by 1.6%. Examining students' trajectories reveals the pathways through which these effects operate: female peers help women persist in their initial STEM programs and encourage those who switch to transfer to other STEM programs rather than leaving STEM entirely. Conversely, male peers push some women out of STEM—either to non-STEM fields or out of higher education entirely.

Peer effects for women in STEM extend well beyond graduation outcomes. Exposure to higher-ability male peers reduces women's subsequent labor market outcomes: a one standard deviation increase in male peer ability decreases employment by 1.0%, earnings by 1.7%, and accumulated work experience by 1.1%. At the same time, women exposed to higher-ability male peers tend to marry higher-ability spouses. This pattern suggests that the observed earnings losses may reflect a combination of reduced persistence in STEM and marriage market dynamics.

Long-term effects are also observed following exposure to higher-ability female peers for women in STEM, though these effects are generally weaker and less precisely estimated for labor market outcomes. While higher-ability female peers do not significantly improve women's employment or earnings, they do affect family formation decisions. In particular, a one standard deviation increase in female peer ability reduces the probability that a woman has a child by age 29 by 2.4% and decreases the number of children by 1.5%, a pattern consistent with women shifting greater focus toward career development.

These effects are specific to women in STEM, indicating that peer ability effects do not operate uniformly across all fields. For women in non-STEM fields, we find no significant effects on graduation outcomes. While there is some evidence that higher-ability male peers decrease earnings and higher-ability female peers decrease fertility, these effects are considerably smaller in magnitude than those observed in STEM. For men, peer ability has little impact on long-term outcomes overall. The main exception is a negative effect on graduation when men are in the minority in non-STEM fields, though these effects are smaller than those for women in STEM and do not translate into significant labor market effects. Taken together, these results highlight that peer ability effects are particularly salient for women in STEM.

Examining these questions requires a setting that allows us to isolate peer effects while tracking students over extended periods. The Chilean higher education system offers unique advantages in this regard. First, to the best of our knowledge, this is the first paper to study peer effects across multiple higher education institutions, covering 33 universities and over 100 college majors serving students from diverse socioeconomic backgrounds and ability levels. This breadth not only addresses concerns about external validity raised by studies focusing on highly selective colleges or military academies, but also allows us to compare peer effects across fields — particularly between STEM and non-STEM programs — which is central to understanding where peer composition matters most. Second, we have access to comprehensive administrative data on students' baseline characteristics and long-term outcomes including graduation, employment, earnings, fertility, and marriage, allowing us to examine effects that extend far beyond educational attainment without relying on survey data. Third, as noted above, the institutional structure in which students enroll directly into specific programs creates well-defined peer groups that share 80%–99% of their courses throughout their academic careers.[6] This stands in contrast to studies relying on random roommate assignment, where peers may follow very different paths and whose academic relevance has been questioned.[7]

[4] For related evidence on peer sex composition, see Booth et al. (2018), Hampole et al. (2026), Thomas (2024) and Zölitz and Feld (2021) for college settings in other fields and Anelli and Peri (2019), Brenøe and Zölitz (2020), Goulas et al. (2018), Hill (2015), Schneeweis and Zweimüller (2012) for high school contexts.

[5] A large experimental literature shows that women's willingness to compete and performance in competitive settings are lower in mixed-gender environments than in single-sex settings (Gneezy et al., 2009; Kamas & Preston, 2012; Niederle & Vesterlund, 2007, 2008). These patterns are shaped by social norms and context, including early exposure to male peers (Booth & Nolen, 2012a, 2012b) and whether actions are observed by male peers (Bursztyn et al., 2017).

[6] We examined curriculum requirements across representative programs (Engineering, Biology, Physics, Psychology, Sociology, Journalism, Business, Medicine, and Pharmacy) at major universities (PUC, UChile, UTFM, and Usach) and found that core mandatory courses account for 80%–99% of total coursework across both STEM (range: 0.80–0.98) and non-STEM programs (range: 0.82–0.99), ensuring substantial course overlap among program peers.

[7] The use of random roommate assignment was inaugurated by Sacerdote (2001) and Zimmerman (2003), and followed by many others (e.g., Foster, 2006; Han & Li, 2009; Hayashi, 2016; Kremer & Levy, 2008; Stinebrickner & Stinebrickner, 2006; Zhang & Pu, 2017). Although roommates often become friends, the frequent failure to identify robust peer effects on academic achievement has raised questions about whether roommates constitute peers of "potential influence" (Stinebrickner & Stinebrickner, 2006). Some studies have examined peer effects in military academies using random assignment to companies or squadrons (Carrell et al., 2009; Lyle, 2007), though these findings may not generalize to other higher education settings.

While these institutional features create well-defined peer groups, estimating causal peer effects remains challenging because individuals are rarely assigned to peer groups at random. To the extent that similar students enroll in the same program, we might mistakenly attribute to peer influence what is really the result of peers being similar, or "correlated effects" (Manski, 1993). In our setting, student selection has two dimensions: students choose which programs to apply to and programs select students from their applicant pools. To address self-selection by students, we exploit variation in peer characteristics across cohorts within programs, a strategy common in the peer effects literature.[8] To address selection by programs, we leverage Chile's centralized admission system in which oversubscribed programs assign seats exclusively based on standardized test scores. Since this represents selection on observables, we control for students' test scores and, in the spirit of Dale and Krueger (2002), for their ranked application preferences. To support our identification strategy, we show that variation in peer composition across cohorts within programs does not correlate with changes in predetermined individual characteristics.

Our paper contributes to several strands of literature. First, we build on an extensive body of work studying peer effects in higher education with a focus on sex. Existing research has primarily examined peer sex composition — specifically, the share of female peers — with growing evidence that having more female peers facilitates success in male-dominated environments, increasing women's academic performance and career outcomes (Booth et al., 2018; Bostwick & Weinberg, 2022; Hampole et al., 2026; Karpowitz et al., 2024). Some studies, however, suggest that a higher share of female peers may steer women toward female-dominated majors, potentially lowering their future earnings (Thomas, 2024; Zölitz & Feld, 2021). A smaller literature has examined peer ability. Fischer (2017) finds that higher-ability peers may push women out of STEM fields, though without distinguishing between male and female peer ability. Feld and Zölitz (2022) makes this distinction in a business school setting but finds no significant effects.

We extend this work in several ways. Like Feld and Zölitz (2022), we separately examine the ability of male versus female peers, but we do so across multiple fields in a broader college context and track long-term post-graduation labor market outcomes using administrative data. Unlike prior work, we find substantial effects: high-ability male and female peers have opposite effects on women in STEM. More importantly, our findings reveal that peer ability may matter more than peer sex composition for understanding women's outcomes. While we control for female share, peer ability effects are substantially larger in magnitude and extend to long-term labor market outcomes, fertility, and marriage—suggesting that examining the ability composition of male and female peers separately provides important insights beyond overall sex composition. We also show that peer effects are highly context-dependent: they are concentrated among women in STEM with minimal effects for women in non-STEM or for men. This heterogeneity helps explain mixed findings in prior work and underscores the importance of examining peer characteristics beyond composition in specific educational contexts.

Beyond the peer effects literature, our findings also speak to the broader discussion on the determinants of sex disparities in STEM (Kahn & Ginther, 2017). A substantial body of research has documented that women in STEM fields face particular challenges: they switch majors more frequently and are more likely to leave STEM than comparable men (Astorne-Figari & Speer, 2019). These patterns do not appear to stem from differences in preparation (Arcidiacono et al., 2012), but may instead reflect differences in competitiveness (Buser et al., 2014), the academic environment (Kugler et al., 2017), faculty gender composition (Carrell et al., 2010; Hoffmann & Oreopoulos, 2009; Rask & Bailey, 2002), labor market expectations (Gemici & Wiswall, 2014; Zafar, 2013), and preferences for grades (Ost, 2010; Rask & Tiefenthaler, 2008). Our findings highlight that peer composition — specifically, the ability levels of male versus female peers — is an additional factor contributing to women's underrepresentation in STEM.

These results offer implications for policy interventions aimed at promoting gender equity in STEM fields. Our findings suggest that interventions aimed at increasing women's exposure to high-achieving female peers could improve their persistence in STEM fields. At the same time, our results point to the importance of understanding and managing peer dynamics in ways that mitigate the potential negative effects that women may experience from high-achieving male peers in STEM environments. While the specific mechanisms and optimal policy designs warrant further investigation, our results underscore that interventions should consider not just the sex composition of student cohorts, but also the ability distribution across sexes when designing programs to promote gender equity in higher education.

2. Theoretical effects of peer ability

We begin with a brief theoretical discussion about potential channels through which peer ability can influence individual outcomes (Epple & Romano, 2011; Sacerdote, 2011). We focus on six key mechanisms: learning spillovers, networks, norms and expectations, self-perception and confidence, classroom instruction and dynamics, and competition. For each of these mechanisms, we discuss the potential mediating role of gender.

Learning Spillovers. High-achieving peers can enhance the learning environment by sharing knowledge, offering insights during discussions, or collaborating effectively on group tasks. These interactions can directly increase an individual's human capital by providing access to better information and study practices

Gender plays a critical role in this channel, as social ties are often stronger among same-sex peers, leading to more frequent interactions and greater opportunities for knowledge exchange and collaboration. Additionally, students may benefit more from same-sex peers due to comfort in communication or shared experiences. For example, women might feel more at ease asking questions or seeking help from other women, especially in male-dominated fields like STEM.

Networks. Beyond immediate academic interactions, high-achieving peers can influence future outcomes through the value of social networks. Peers who excel academically often have access to better opportunities, such as prestigious internships, jobs, or advanced academic programs. Being part of a high-achieving peer group can provide individuals with valuable connections, mentorship, and access to professional networks, which can significantly impact long-term career trajectories.

Gender dynamics play a key role in determining how individuals access and benefit from these networks. As with learning spillovers, this mechanism is likely to be more relevant among same-sex peers due to homophily. In male-dominated fields, women may face additional barriers to accessing influential networks if these networks are dominated by men, leading to fewer opportunities for mentorship or career advancement. Conversely, high-achieving female peers can serve as critical gateways to professional opportunities for other women, helping to build more inclusive and supportive networks.

Norms and Expectations. Higher-achieving peers can also influence outcomes by setting new norms and expectations for academic performance and career aspirations. When surrounded by high-performing peers, students may internalize these standards, striving to match their peers' achievements. This can lead to higher motivation and effort, ultimately improving outcomes.

[8] See for instance Angrist and Lang (2004), Bifulco et al. (2014), Black et al. (2013), Cools et al. (2022), Gould et al. (2009), Hoxby (2000b), Lavy et al. (2012), Lavy and Schlosser (2011), Merlino et al. (2019) and Olivetti et al. (2020).

Gender is likely to mediate this effect by shaping individuals' reference groups, particularly in contexts where gender is salient. Same-sex peers often serve as the most relevant reference group, as individuals are more likely to identify with those who share similar social identities. For women in STEM fields, this means that same-sex peers can play a critical role in setting norms and expectations, providing benchmarks that resonate more closely with their own experiences.

Self-Perception and Confidence. Peer ability can also shape outcomes by influencing self-perception and confidence. Interactions with high-achieving peers can alter a student's assessment of their own abilities, either positively or negatively. For example, seeing peers succeed might boost confidence by demonstrating what is possible, or it could undermine confidence by creating unfavorable comparisons.

Gender plays a significant role here as well. Women, particularly in male-dominated fields, may be more susceptible to confidence effects due to stereotypes and societal expectations (Ost, 2010; Rask & Tiefenthaler, 2008). For instance, high-achieving male peers may unintentionally reinforce stereotypes about gender differences in ability, leading women to doubt their own potential. On the other hand, high-achieving female peers can serve as powerful role models, helping women build confidence and resilience.

Classroom Instruction and Dynamics. Peer ability may also influence outcomes through changes in classroom instruction and the overall learning environment. A growing body of research shows that teachers may adapt or target their teaching depending on the composition of the peer group (Duflo et al., 2011; Jackson, 2018). These studies highlight that instruction is not fixed: teachers modify the pace, the content they emphasize, and the level of individual support they provide depending on the distribution of student ability. More generally, the literature suggests that teaching is easier in more homogeneous classrooms, while heterogeneous groups create additional challenges for instructors. Under this channel, lower-ability students may be disadvantaged in classrooms with many high-ability peers if instruction becomes less aligned with their needs.

Peer composition can also affect the instructional environment indirectly. Although the existing evidence does not focus specifically on peer ability, several studies show that changes in peer composition — such as the presence of more disruptive students or shifts in sex composition — alter classroom climate (Carrell & Hoekstra, 2010; Lavy & Schlosser, 2011). These findings suggest that classroom dynamics are sensitive to who is present in the room, providing a plausible channel through which peer ability could also influence how instruction is delivered and absorbed.

Competition. Finally, peer ability can also influence outcomes through competition and concerns about ranking. Students often compare themselves to their peers, and the desire to outperform others can drive academic effort. However, this effect is complex and deeply intertwined with self-confidence. A student's perception of their ability to compete plays a pivotal role: high-performing peers may motivate those who are confident in their abilities to work harder, but they might discourage students with lower self-confidence, who may feel unable to compete effectively. Thus, the impact of competition depends not only on a student's position in the ranking but also on whether they perceive themselves as capable of rising to the challenge.

Sex differences are particularly salient in this channel. Women, for instance, may experience competition differently from men, especially in competitive environments like STEM. Self-confidence plays a critical role in shaping these experiences. Women with low self-confidence may find the heightened competitive atmosphere discouraging, perceiving themselves as less capable of succeeding. In fact, research has shown that women tend to be more averse to competition and underperform in competitive environments, displaying a lower degree of self-confidence about their own abilities (Gneezy et al., 2009; Niederle & Vesterlund, 2007; Rask & Tiefenthaler, 2008). Societal stereotypes about gender and competition further complicate this dynamic, as they can reinforce feelings of inadequacy or pressure women to conform to norms that discourage competitive behavior.

In sum, peer ability can influence outcomes through multiple mechanisms, each shaped by gender. High-achieving peers can enhance learning, expand professional networks, set aspirational norms, and drive academic effort. However, these benefits may be offset by challenges such as diminished confidence, heightened competitive pressures, or reinforced stereotypes—particularly for women in STEM fields. Same-sex peers are often better positioned to foster collaboration, provide relatable benchmarks, and serve as role models, amplifying the positive effects of peer ability. In contrast, cross-sex interactions, especially with high-achieving male peers, may introduce additional challenges that undermine these potential gains.

3. Institutional setting

The Chilean postsecondary education sector consists of 60 universities that offer college degrees, with programs typically designed to take 5 years to complete, although in practice most students take longer to graduate. Of the total number of universities, 33 participate in a centralized admission system called SUA (for *Sistema Único de Admisión*, or Unified System of Admission).[9] Universities that do not participate in this admission system are predominantly private and typically serve lower-scoring students. The 33 universities that participate in SUA are all non-profit institutions and can be either public or private. These universities span a wide range of selectivity levels.

In this study we focus on students enrolling in one of these 33 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.[10] 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. All programs require scores from the mathematics and language sections of the PSU, as well as high school GPA. Additionally, depending on the program, some require the science section, others the history section, and some accept the higher score between the two. The relative weights assigned to these components vary across programs and over time, as programs have the flexibility to modify them annually. Because of these changing weights, the composition of admitted students within a program may vary across cohorts even when capacity and student preferences remain the same.

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 & 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 students 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.

[9] Before 2012, 25 institutions participated in the centralized admission system. Eight additional institutions joined in 2012.

[10] Prior to 2004, students had to choose among six subject tests, but as of 2004, they must choose between science and history.

Table 1
Descriptive statistics.

	(1) 2003–2013 cohorts (Graduation outcomes)			(2) 2000–2008 cohorts (Other outcomes)			Cohort difference
	Women (1)	Men (2)	W-M (3)	Women (4)	Men (5)	W-M (6)	(1)–(2) (7)
Cohort characteristics							
Cohort size	84.56	106.44	−21.88***	79.65	102.80	−23.15***	4.14***
	78.97	116.39	(0.27)	71.35	107.59	(0.31)	(0.15)
Socioeconomic characteristics							
Mother: Primary	0.11	0.10	0.01***	0.13	0.12	0.01***	−0.02***
	0.32	0.30	(0.00)	0.33	0.32	(0.00)	(0.00)
Mother: Secondary	0.44	0.44	−0.00	0.45	0.45	−0.00***	−0.01***
	0.50	0.50	(0.00)	0.50	0.50	(0.00)	(0.00)
Mother: Tertiary	0.39	0.39	−0.00	0.37	0.37	0.00	0.02***
	0.49	0.49	(0.00)	0.48	0.48	(0.00)	(0.00)
Father: Primary	0.11	0.10	0.01***	0.12	0.11	0.01***	−0.01***
	0.31	0.29	(0.00)	0.32	0.31	(0.00)	(0.00)
Father: Secondary	0.36	0.36	0.00	0.37	0.37	0.00	−0.00***
	0.48	0.48	(0.00)	0.48	0.48	(0.00)	(0.00)
Father: Tertiary	0.39	0.41	−0.02***	0.40	0.42	−0.02***	−0.00***
	0.49	0.49	(0.00)	0.49	0.49	(0.00)	(0.00)
Mother works	0.47	0.47	0.00	0.44	0.44	0.00	0.03***
	0.50	0.50	(0.00)	0.50	0.50	(0.00)	(0.00)
Father works	0.75	0.76	−0.01***	0.76	0.78	−0.01***	−0.02***
	0.43	0.43	(0.00)	0.43	0.42	(0.00)	(0.00)
Mother: Full-time	0.38	0.38	−0.00	0.37	0.37	0.00	0.01***
	0.49	0.49	(0.00)	0.48	0.48	(0.00)	(0.00)
Father: Full-time	0.59	0.62	−0.03***	0.61	0.64	−0.03***	−0.02***
	0.49	0.49	(0.00)	0.49	0.48	(0.00)	(0.00)
Public HS	0.31	0.31	0.00***	0.36	0.36	0.00	−0.05***
	0.46	0.46	(0.00)	0.48	0.48	(0.00)	(0.00)
Voucher HS	0.48	0.45	0.03***	0.42	0.39	0.03***	0.06***
	0.50	0.50	(0.00)	0.49	0.49	(0.00)	(0.00)
Private HS	0.19	0.21	−0.02***	0.20	0.22	−0.02***	−0.01***
	0.39	0.41	(0.00)	0.40	0.41	(0.00)	(0.00)
Academic performance							
Math rank	0.75	0.81	−0.06***	0.76	0.81	−0.06***	−0.01***
	0.18	0.16	(0.00)	0.17	0.16	(0.00)	(0.00)
GPA rank	0.76	0.68	0.08***	0.76	0.67	0.10***	0.00***
	0.21	0.25	(0.00)	0.21	0.25	(0.00)	(0.00)
Language rank	0.77	0.76	0.01***	0.77	0.76	0.01***	0.00
	0.18	0.19	(0.00)	0.18	0.19	(0.00)	(0.00)
Graduation							
Graduates: Any	0.76	0.63	0.12***				
	0.43	0.48	(0.00)				
Graduates: Program	0.55	0.41	0.14***				
	0.50	0.49	(0.00)				
Earnings and employment							
Annual earnings				8795	10,407	−1613***	
				11,564	12,976	(41.20)	
Employed				0.59	0.63	−0.04***	
				0.49	0.48	(0.00)	
Fertility and marriage							
Has child				0.29	0.23	0.06***	
				0.45	0.42	(0.00)	
Married				0.15	0.11	0.05***	
				0.36	0.31	(0.00)	
Obs	259,333	279,205		170,931	187,711		

Notes: This table presents descriptive statistics for our two estimation samples. The first sample (columns 1–3) includes students who enrolled in university programs between 2003 and 2013 and is used to analyze graduation outcomes. The second sample (columns 4–6) includes students who enrolled between 2000 and 2008 and is used to examine earnings, employment, fertility, and marriage outcomes. For each sample, we report means (first row) and standard deviations (second row) for key variables. Columns (3) and (6) report sex differences (Women–Men) within each sample. Column (7) reports the difference between the 2003–2013 cohorts and the 2000–2008 cohorts, estimated from regressions of each characteristic on an indicator for the graduation sample. Standard errors are clustered at the individual level to account for students appearing in both samples. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4. Data and sample description

4.1. Data sources

This study uses a unique dataset that combines administrative records on education, earnings, fertility, and marriage. We constructed this dataset by digitizing hard copies of published test score results from a local newspaper (El Mercurio) and merging them with multiple administrative data sources, achieving a matching rate of over 99%.

Educational records

Our educational data comes from multiple sources. First, we digitized test score results for all students taking the standardized admission test from 1999 to 2011. These records were merged with socioeconomic information that students provide when signing up for admission tests, high school GPA, and university enrollment. To look at graduation outcomes, we complement this with administrative records that capture graduation for all higher institutions in the country for the 2007 to 2024 period.

Labor market outcomes

We obtain earnings records from the unemployment insurance system of Chile's Ministry of Labor for 2007–2017, which tracks monetary contributions to individual unemployment insurance accounts. While this system covers most of the formal sector, it excludes self-employed workers (8% of our sample[11]) and public sector employees.[12] The records are capped at approximately $5000 per month, but this limitation affects less than 1% of individuals in our sample. Although we lack public sector earnings data for most of our study period, we have access to 2019 public sector earnings records.[13] Using these 2019 records, we estimate that public sector employees comprise 16% of our sample. Analysis of this 2019 data reveals that peer effects on public sector earnings follow patterns similar to our main findings, suggesting our inability to observe public sector earnings throughout the study period likely leads us to underestimate the true magnitude of peer effects on labor market outcomes (see Section 6.2).

Fertility and marriage

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.

4.2. Sample construction and description

Our analysis uses two different samples, determined by data availability across outcomes. For graduation outcomes, we study students who enrolled between 2003 and 2013 and follow them for 12 years after initial enrollment. Since graduation records begin in 2007 and programs typically take at least 5 years to complete, 2003 is the earliest cohort for which we can reliably observe graduations. For earnings, fertility, and marriage outcomes, we focus on students who enrolled between 2000 and 2008, whom we observe approximately 10–11 years after enrollment (around age 28). Earnings data are only available through 2017 and fertility data through 2018, which determines both the observation window and the cohorts we can include.

The extended 12-year observation window for graduation is motivated by the fact that actual time to graduation substantially exceeds nominal program durations. While most programs are designed to take five years, some last up to eight years. Additionally, program switching is common (approximately 35% of students switch at least once), and degree conferral typically occurs one year after completing coursework due to administrative procedures. Fig. 1 shows cumulative graduation rates by years since enrollment, both for graduation from any university program and from the initial program of enrollment, illustrating that a share of students continue to graduate well beyond the standard program length. Since we have graduation records through 2024, we can afford to wait 12 years to capture the vast majority of eventual graduations.

For the earnings, fertility, and marriage sample, we observe students at approximately 10–11 years after enrollment. Although observing outcomes at later career stages would be ideal, this observation window allows us to capture a point at which 90% of individuals have either graduated or left higher education and are likely participating in the labor market. Note that graduation reflects formal degree conferral rather than coursework completion, so some of the remaining 10% may also be working.[14]

Across both samples, we classify programs into STEM and non-STEM categories using OECD field classifications. We define STEM broadly to include technology, engineering, physical sciences, life sciences, mathematics and statistics, and related applied fields.[15]

Our graduation sample includes 538,538 students across 1378 programs, and our earnings sample includes 358,644 students across 959 programs. Both samples form unbalanced panels, as not all programs are observed throughout the entire period—some programs open or close during our observation window. On average, we observe each program in 7 out of 11 years in the graduation sample and in 7 out of 9 years in the earnings sample.

Table 1 shows descriptive statistics for both samples. There are on average 93 students in each program cohort. A little less than half of the students in our sample are women. Regarding family background, around 38% of students have mothers with tertiary education and 40% have fathers with tertiary education. Average labor force participation is 46% for mothers and 76% for fathers. The distribution across high school types shows that 34% of students attended public schools (typically serving low-income families), 44% attended voucher schools (serving the middle class), and 20% attended private schools (serving the elite).

Men and women come from similar socioeconomic backgrounds in terms of parental education and labor force participation. Women are slightly more likely than men to have attended voucher schools in both samples (48% vs. 45% in the 2003–2013 cohorts and 42% vs. 39% in the 2000–2008 cohorts), while men are slightly more likely to have attended private schools (21% vs. 19% in both samples). The 2003–2013 cohorts are broadly similar to the 2000–2008 cohorts, though the more recent cohorts have slightly larger average class sizes (95 vs. 91 students) and a higher share of students from voucher schools (47% vs. 41%), consistent with the expansion of this sector over time.

Average math, language, and GPA ranks are around the 75th percentile. This is to be expected considering that not all students taking the test end up enrolling in college, and that institutions participating in the centralized admission process typically attract higher-scoring candidates. Although these universities collectively span a wide range of selectivity levels, the programs within our sample still represent a more selective segment of higher education in Chile compared to non-participating institutions. Looking at sex differences in admissions scores, men tend to outperform women in math (81st vs. 76th percentile), while women have a small advantage in language (77th vs. 76th percentile) and a larger advantage in high school GPA (76th vs. 68th percentile).

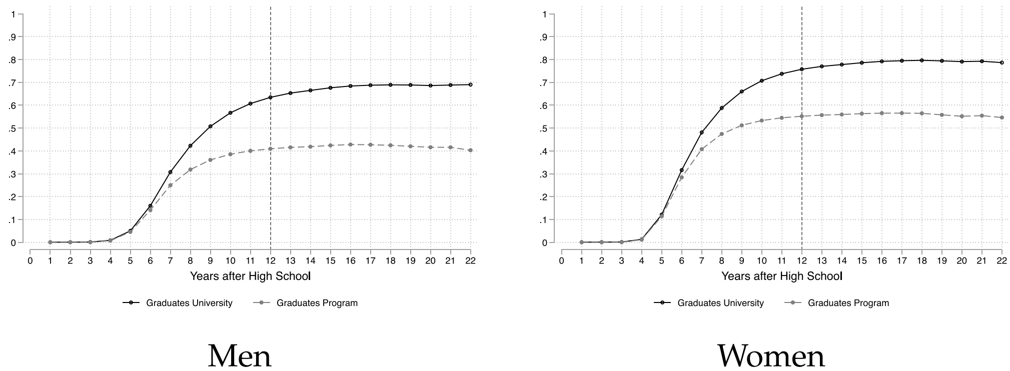
[11] According to data from the Chilean household survey for 2017 (Casen, 2017) 8% of individuals aged 25 to 30 who graduated from college are self-employed.

[12] The data also excludes workers with training contracts, workers under 18, those in domestic service, and pensioners, though these categories should not affect our sample.

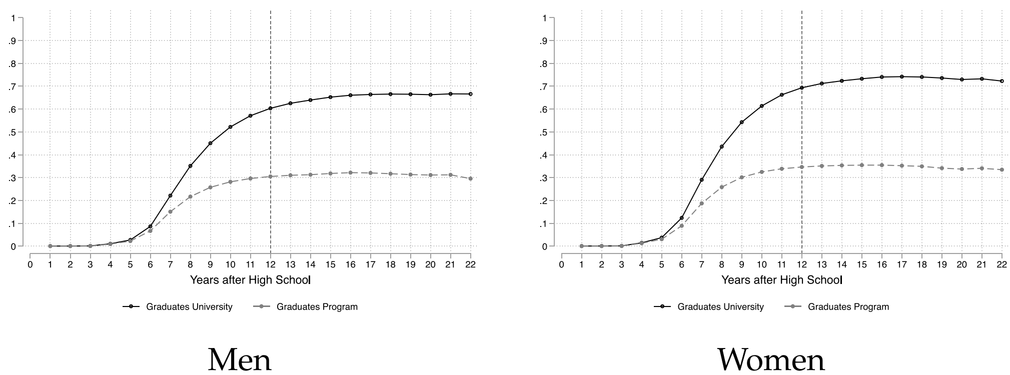
[13] Data on public sector employees was collected from https://www.portaltransparencia.cl and contains information for 639,797 employees in 2019 These records exclude the police, military and armed forces.

[14] The treatment itself could affect the probability of remaining enrolled at this point. We find that exposure to higher-ability male peers does not significantly affect this probability after 10 years, while exposure to higher-ability female peers slightly decreases it for women. This could lead us to overestimate the effect of female peers on earnings, as those who remain enrolled are not yet earning labor market income.

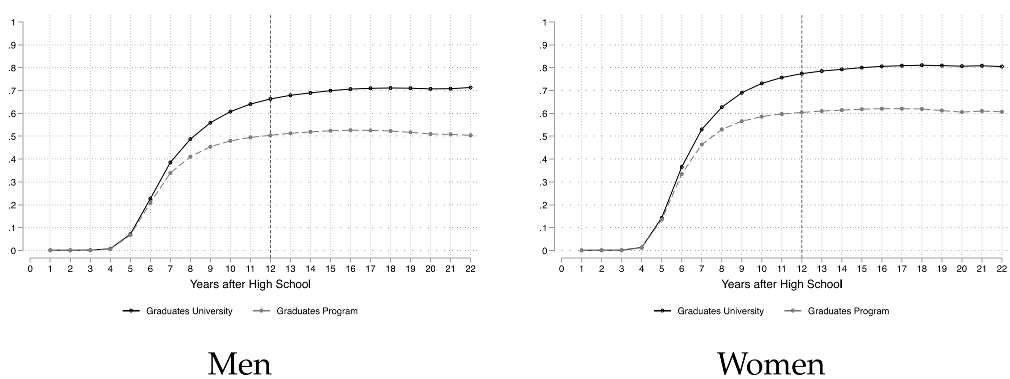
[15] Specifically, we classify as STEM all programs in the OECD broad fields of Sciences (Physical Sciences, Mathematics and Statistics, Computer Science, Life Sciences) and Engineering, Manufacturing and Construction (Engineering and Engineering Trades, Manufacturing and Production), plus three service fields (Environmental Protection, Security Services, Transport Services) that are classified under Technology and Basic Sciences in the UNESCO ISCED classification. We exclude Architecture from STEM and classify it as non-STEM.



(a) All programs



(b) STEM programs



(c) Non-STEM programs

Fig. 1. Cumulative graduation rates by years since enrollment.
Notes: This figure shows cumulative graduation profiles by years since enrollment. Each panel plots the probability of graduating from any university program (solid line) and from the initial program (dashed line). The vertical line marks 12 years since enrollment. The sample includes students enrolled between 2003 and 2013 who are in the estimation sample.

Twelve years after enrolling, around 70% of students have graduated from any university program, while 48% have graduated from their initial program. Women are substantially more likely than men to graduate from any program (76% vs. 63%) and from their initial program (55% vs. 41%). Regarding labor market outcomes measured 10 years after enrollment, average annual earnings (including zeros for the unemployed) are $9601, with women earning $8795 and men $10,407. About 61% of students are employed in the private sector. Among those who work, annual earnings average around $14,400. For family formation outcomes measured 11 years after enrollment, 26% of students have had a child (29% of women vs. 23% of men) and 13% have married (15% of women vs. 11% of men).

5. Empirical strategy

Our identification approach exploits variation across years and within-program in male and female peers' test scores, a strategy com-

Table 2
Balance test: Peer characteristics and individual pre-determined characteristics.

	2003–2013 cohorts (Graduation outcomes)				2000–2008 cohorts (Other outcomes)			
	Women		Men		Women		Men	
	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	−0.02	−0.02	0.01	0.02	−0.04	−0.02	−0.01	0.05
	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
	[246,684]	[246,684]	[263,338]	[263,338]	[169,588]	[169,588]	[185,530]	[185,530]
Mother: Secondary	−0.02	0.01	−0.01	−0.00	−0.01	−0.01	−0.03	0.00
	(0.04)	(0.03)	(0.03)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
	[246,684]	[246,684]	[263,338]	[263,338]	[169,588]	[169,588]	[185,530]	[185,530]
Mother: Tertiary	0.03	0.01	−0.01	−0.02	0.05	0.02	0.03	−0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
	[246,684]	[246,684]	[263,338]	[263,338]	[169,588]	[169,588]	[185,530]	[185,530]
Father: Primary	−0.02	−0.02	0.02	−0.00	−0.09***	−0.02	−0.02	0.04
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
	[246,684]	[246,684]	[263,338]	[263,338]	[169,588]	[169,588]	[185,530]	[185,530]
Father: Secondary	0.01	0.02	−0.01	−0.00	0.03	0.01	−0.02	−0.11**
	(0.04)	(0.03)	(0.03)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
	[235,234]	[235,234]	[253,732]	[253,732]	[160,257]	[160,257]	[177,097]	[177,097]
Father: Tertiary	−0.00	0.00	−0.02	−0.03	0.03	0.01	0.02	0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)	(0.04)	(0.05)
	[235,234]	[235,234]	[253,732]	[253,732]	[160,257]	[160,257]	[177,097]	[177,097]
Mother works	0.02	0.02	0.01	0.00	−0.00	0.02	−0.01	0.01
	(0.04)	(0.03)	(0.03)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
	[245,804]	[245,804]	[262,601]	[262,601]	[168,933]	[168,933]	[184,869]	[184,869]
Father works	−0.02	0.02	−0.04	0.04	0.00	−0.00	−0.01	0.04
	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
	[229,225]	[229,225]	[248,300]	[248,300]	[156,761]	[156,761]	[173,778]	[173,778]
Mother: Full-time	0.05	0.02	−0.01	0.00	0.01	0.01	−0.01	0.01
	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
	[245,804]	[245,804]	[262,601]	[262,601]	[168,933]	[168,933]	[184,869]	[184,869]
Father: Full-time	−0.01	−0.01	−0.05	0.03	0.00	0.03	−0.02	0.03
	(0.04)	(0.03)	(0.03)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
	[229,225]	[229,225]	[248,300]	[248,300]	[156,761]	[156,761]	[173,778]	[173,778]
Public HS	−0.02	0.02	−0.01	0.03	0.01	−0.00	−0.05	0.05
	(0.04)	(0.03)	(0.03)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
	[256,357]	[256,357]	[275,015]	[275,015]	[171,952]	[171,952]	[188,754]	[188,754]
Voucher HS	0.00	−0.02	0.00	−0.02	−0.04	−0.03	0.03	−0.12**
	(0.04)	(0.03)	(0.03)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
	[256,357]	[256,357]	[275,015]	[275,015]	[171,952]	[171,952]	[188,754]	[188,754]
Private HS	0.02	−0.00	−0.01	−0.01	0.03	0.02	0.03	0.06*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.04)
	[256,357]	[256,357]	[275,015]	[275,015]	[171,952]	[171,952]	[188,754]	[188,754]

Notes: This table tests whether student characteristics are correlated with female and male peer ability. Each cell shows the coefficient from a separate regression of the row variable on the mean rank of female peers (odd columns) or male peers (even columns). All specifications include program fixed effects, major-by-cohort and university-by-cohort fixed effects, preference controls, and controls for students' own test scores. We test these correlations for two samples: students who enrolled between 2003–2013 (used for analyzing graduation outcomes) and those who enrolled between 2000–2008 (used for analyzing earnings, fertility, and marriage outcomes). Standard errors clustered at the program level are shown in parentheses. Number of observations shown in brackets. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

monly used in the peer effects literature.[16] Let y_{ijmt} denote the outcome of interest for student i enrolled in program j within major m at university u in cohort t, measured ten to twelve years after college enrollment (the exact timing varies depending on the outcome examined). We define majors using the OECD subarea classification system, which includes 24 categories.[17] Our baseline econometric specification is:

$$y_{ijmut} = \alpha + \beta_f \bar{s}^{f}_{ijmut} + \beta_m \bar{s}^{m}_{ijmut} + \beta_{fs} f s_{ijmut} + \gamma s_{ijmut} + \lambda X_{ijmut} + \mu_j + \eta_{mt} + \kappa_{ut} + \sum_{r=1}^{8} \delta_{p_{ir}} + \epsilon_{ijmut}, \quad (1)$$

where s_{ijmt} is a measure of individual ability for student i, defined as the student's rank in the distribution of math admission test scores

[16] See, for instance, Angrist and Lang (2004), Bifulco et al. (2014), Black et al. (2013), Cools et al. (2022), Gould et al. (2009), Hoxby (2000a), Lavy et al. (2012), Lavy and Schlosser (2011), Merlino et al. (2019) and Olivetti et al. (2020).

[17] These categories span eight broad areas: Agriculture (including Veterinary); Sciences (Life Sciences, Physical Sciences, Computer Science, Mathematics and Statistics); Social Sciences and Law (Social and Behavioral Sciences, Law, Business and Administration, Journalism and Information); Education (Education Science, Teacher Training); Humanities and Arts; Engineering and Construction (Architecture and Construction, Manufacturing and Production, Engineering and Engineering Trades); Health (Medicine, Social Services); and Services (Environmental Protection, Security Services, Transport Services, Personal Services).

Table 3
Variation in peer math rank: Raw and residual variation.

	2003–2013 cohorts (Graduation outcomes)				2000–2008 cohorts (Other outcomes)			
	Women		Men		Women		Men	
	Female peers (1)	Male peers (2)	Female peers (3)	Male peers (4)	Female peers (5)	Male peers (6)	Female peers (7)	Male peers (8)
Raw variation								
Mean	0.752	0.777	0.784	0.809	0.757	0.782	0.789	0.814
SD	0.138	0.135	0.136	0.127	0.138	0.134	0.135	0.124
Min	0.206	0.218	0.233	0.122	0.219	0.218	0.286	0.122
Max	0.997	0.999	0.996	0.998	0.997	0.999	0.996	0.997
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	0.029	0.035	0.033	0.027	0.028	0.035	0.032	0.026
Min	−0.380	−0.273	−0.325	−0.382	−0.396	−0.267	−0.358	−0.398
Max	0.379	0.363	0.418	0.403	0.347	0.262	0.391	0.389

Notes: This table presents the variation in average math rank for male and female peers. "Raw Variation" shows the unadjusted variation in peer math rank. "Net of Program and Cohort Fixed Effects" displays the residual variation after partialling out program fixed effects, major-by-cohort and university-by-cohort fixed effects; this residual variation is the source of identification in our empirical strategy. Statistics shown separately for women and men in both samples: 2003–2013 cohorts (graduation outcomes) and 2000–2008 cohorts (labor market and family outcomes).

within cohort t.[18] The academic ability of female and male peers, $\overline{s}^{f}_{ijmt}$ and $\overline{s}^{m}_{ijmt}$, corresponds to the leave-one-out average of individual ability among female and male students enrolled in the same program-cohort cell, excluding student i. We focus on math rank rather than language scores because math scores are a strong predictor of long-term outcomes, while language scores are not (see Appendix Table A.1).

We also control for the share of female students among individual i's peers, fs_{ijmut}, which is calculated as the proportion of female students in the program-cohort cell excluding student i. Including this control allows us to separate the effect of peer ability from the effect of overall sex composition, ensuring that our estimates of β_f and β_m capture the impact of having higher-ability female or male peers conditional on the sex composition of the program. This is important given evidence that sex composition itself can affect educational outcomes (Booth et al., 2018; Bostwick & Weinberg, 2022; Hampole et al., 2026).[19]

The vector X_{ijmut} includes individual characteristics such as parents' education and employment status, family composition, family income, test score performance across all subjects (math, language, science, and history), and high school GPA. Controlling for students' own math rank not only improves efficiency but also eliminates the *exclusion bias* arising from the mechanical negative correlation between own test scores and the leave-out means (Caeyers & Fafchamps, 2020).

The model includes a comprehensive set of fixed effects designed to isolate quasi-random variation in peer composition. First, program fixed effects (μ_j) control for time-invariant characteristics of each program that attract certain types of students. Second, major-by-cohort (η_{mt}) and university-by-cohort (κ_{ut}) fixed effects account for temporal shocks affecting the composition of students entering specific majors or universities in a given year. Finally, in the spirit of Dale and Krueger (2002), we include fixed effects for students' ranked application preferences over university-major combinations. Specifically, $\delta_{p_{ir}}$ represents a fixed effect for the university-major combination p_{ir} that student i listed in their rth preference position. For each ranking position r (from 1 to 8), we include a separate fixed effect for the university-major pair listed in that position. There are 617 unique university-major combinations in our data. These preference fixed effects allow us to control for unobserved student characteristics such as ambition, ability, and motivation that are not fully captured by test scores. Since admission in Chile is centralized and entirely determined by test scores, controlling for all admission test scores and rankings of preferences serves an analogous purpose to controlling for the set of schools where students applied and were admitted, as in Dale and Krueger (2002).

The identification strategy relies on the assumption that, after conditioning on program fixed effects, cohort fixed effects, preference fixed effects, and individual characteristics, peer assignment is as good as random. Formally, we assume:

$$\varepsilon_{ijmut} \perp \overline{s}^{f}_{ijmut}, \overline{s}^{m}_{ijmut} \mid \mu_j, \eta_{mt}, \kappa_{ut}, \{\delta_{p_{ir}}\}_{r=1}^{8}, s_{ijmut}, X_{ijmut}$$

This assumption requires that students cannot anticipate the specific composition of their cohort when choosing their program. While students select programs based on general characteristics — including the typical profile of enrollees — they cannot foresee the particular peer ability of their specific cohort, as this is determined only after admission decisions are made. Our identification thus exploits unanticipated year-to-year variation in peer composition within programs.

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 validate our identification strategy, we conduct several tests. First, we assess whether peer assignment is conditionally random by testing for balance on predetermined characteristics. Second, we document the sources and magnitude of variation in peer ability that our strategy exploits. Third, we verify that male and female peer ability vary independently, which is necessary to separately identify their effects. Finally, we confirm that our results are robust to alternative specifications and sample restrictions.

Starting with the balance tests, we estimate Eq. (1) using predetermined 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 indicate that peer assignment is not as good as random. The results, shown in Table 2, are largely consistent with

[18] We use ranks instead of raw test scores to avoid issues related to changes in test score scaling over time.

[19] Our main results remain substantively unchanged when we exclude this control from the specification, suggesting that peer ability effects operate independently of overall sex composition.

quasi-random assignment of peers. Most coefficients are small in magnitude and statistically insignificant. While a few isolated correlations reach statistical significance — notably, father's primary education is negatively correlated with female peer ability for women (−0.09), and voucher high school attendance shows a negative correlation with male peer ability for men (−0.12) — these represent isolated cases rather than systematic patterns. Importantly, these correlations do not consistently favor one direction, and Appendix Tables A.2 and A.3 show that similar patterns hold when we restrict the sample to STEM or non-STEM programs. To improve the efficiency of our estimates, our full econometric specification controls for these covariates at the individual level. Furthermore, the inclusion of these covariates does not significantly affect our estimates, providing further support for our empirical strategy.

Turning to the sources of variation, our identification strategy exploits year-to-year fluctuations in peer ability that stem from three sources: changes in program preferences, program capacity adjustments, and changes in how programs weight admission criteria when calculating applicants' final scores. Importantly, while we focus on math rank, programs consider multiple admission criteria — math, language, science or history test scores, and GPA — with varying weights over time. These varying weights, combined with capacity constraints driven by institutional decisions, provide our source of variation. It is worth noting that while math rank strongly predicts long-term outcomes, other admission criteria like language or history scores do not (see Appendix Table A.1).

Table 3 details the variation in male and female peers' average math rank. For women, the average rank of female peers is 0.76, while the average rank of male peers is 0.78. Men tend to have slightly higher-performing peers, with an average rank of male peers of 0.81 and female peers of 0.79. The standard deviation of peer ability is approximately 0.13 across all groups. After controlling for all the fixed effects and individual characteristics in our main specification (Eq. (1)), the residual variation averages 0.03 across groups, accounting for approximately one-fifth of the overall raw variation. Appendix A reports similar variation in peer characteristics among students enrolling in STEM and non-STEM programs.

A third requirement is that the average math rank of male and female peers not be perfectly correlated with each other. Our analysis confirms this condition holds in the data. After controlling for all the fixed effects and individual characteristics in our main specification (Eq. (1)), the correlation between male and female peer ability is far from perfect (see Appendix Figure A.1). In fact, approximately 36% of program-year observations show male and female peer ability moving in opposite directions. This divergence stems from sex differences in performance across admission criteria. Women typically outperform men in high school GPA, while men tend to score higher on math tests. When programs adjust their admission weights — for example, decreasing the weight on math scores while increasing the weight on high school GPA — this allows women with relatively lower math scores to gain admission compared to men. These weight adjustments thus create independent variation in the math rank of male versus female peers within the same program over time.

Finally, we confirm that our results are not driven by specific modeling choices or sample composition. Appendix Tables A.5 and A.6 show that our estimates remain stable across five alternative specifications: (1) a baseline model with only program and year fixed effects; (2) our main specification including major-by-year and university-by-year fixed effects along with preference controls; (3) our main specification replacing the ordered preference fixed effects with dummies indicating whether each university-major combination appears anywhere among the student's top four preference choices, regardless of order[20]; (4) a balanced panel restriction requiring programs to appear in all years; and (5) our main specification augmented with program-specific linear time trends.

[20] This cutoff is motivated by the fact that 92% of students in our sample are admitted to one of their top four ranked programs.

6. 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.

6.1. Effects of peer ability on college graduation

We begin by studying the effect of peers on college graduation. Table 4 reports estimates of the effect of male and female peers' average math rank, as well as the share of female students among peers, on students' likelihood of graduating from a university program. Specifically, we examine five probabilities: graduating from any university program, graduating on-time (i.e., within the program's official duration plus one year[21]), graduating from a STEM program, graduating from a non-STEM program, and graduating from the program they first enrolled in. Twelve years after high school, on average, 76% of women and 63% of men in our sample have graduated from a university program, 48% of women and 31% of men have graduated on time, and 55% of women and 41% of men have graduated from the program where they first enrolled. Note that the sum of the probabilities of graduating from STEM and non-STEM can exceed the probability of graduating from any program because some students graduate from both a STEM and a non-STEM program (0.2% of students in our sample).

To better understand these outcomes, it is useful to consider the different paths students can take after initial enrollment. Students who remain in their initial program may either graduate or drop out. Alternatively, students may transfer to a different program — either within the same field or to a different field (STEM or non-STEM) — and subsequently graduate or drop out from that program. As noted earlier, a significant share of students in our sample transfer at least once: 30% of women and 39% of men, with most transferring only once. Fig. 2 illustrates these possible trajectories.

To provide a more complete picture of how peers affect different pathways, Table 5 decomposes outcomes into mutually exclusive and exhaustive categories: staying in the initial program (graduating or dropping out), switching fields, and switching to STEM or non-STEM programs (with subsequent graduation or dropout).[22] While most estimates in Table 5 are not statistically significant due to these more granular outcomes, we interpret the coefficients to understand the underlying trajectories that drive the main results in Table 4.

Our main findings reveal that peer ability effects are concentrated among women in STEM fields, where peer ability significantly shapes educational outcomes. For women who initially enrolled in STEM programs, higher-ability female peers substantially improve persistence and success through two main channels: by helping them graduate from their initial STEM programs and by encouraging those who switch to transfer to other STEM programs rather than leaving STEM entirely. In stark contrast, higher-ability male peers decrease women's probability of graduating from STEM programs, pushing some women out of STEM either to non-STEM fields or out of higher education entirely. Outside of this group, peer ability effects are considerably more limited. For women in non-STEM programs, we find no significant effects of peer ability on graduation outcomes. For men, peer ability has minimal impact on outcomes in STEM fields, where they constitute the majority.

[21] As noted earlier, students typically obtain their degree one year after completing coursework due to administrative procedures required for degree conferral.

[22] To construct these outcomes, we track students' enrollment across all programs over time and classify them based on their final outcome. When a student enrolls in multiple programs or switches more than once, we prioritize STEM graduations over non-STEM graduations, and completed degrees over non-completion. This classification approach means that some outcomes in Table 5 may not exactly match those in Table 4, as the latter does not impose mutual exclusivity across outcomes.

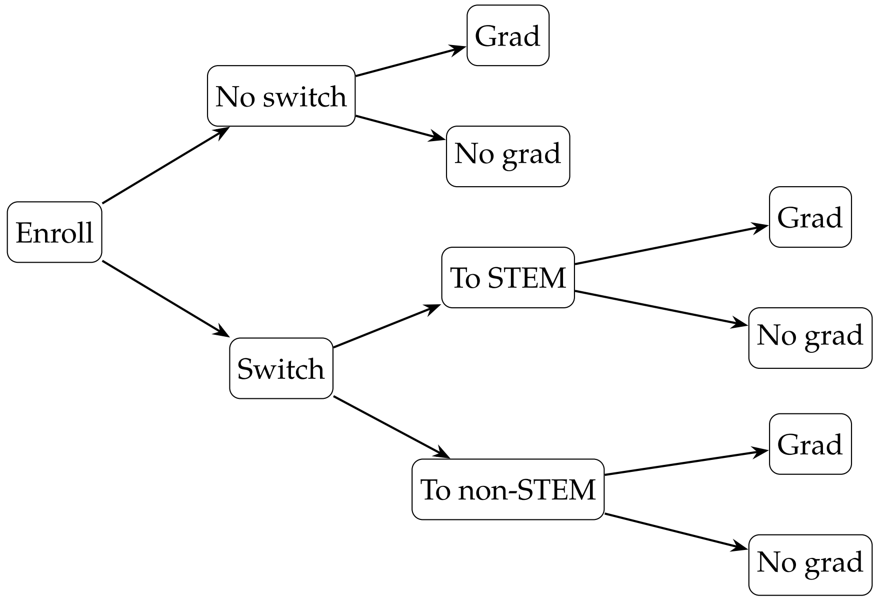


Fig. 2. Student trajectories after initial enrollment.
Notes: This figure illustrates the possible trajectories for students after initial enrollment, corresponding to the outcome structure analyzed in Table 5. Students either remain in their initial program or switch fields. Conditional on switching, students move to STEM or non-STEM programs and may or may not graduate.

We do observe some evidence that higher-ability female peers negatively affect men's graduation outcomes in non-STEM fields where men are the minority, a pattern consistent with students being negatively affected by higher-ability opposite-sex peers when in the sex minority, though these effects are substantially smaller in magnitude than those observed for women in STEM.

We begin by analyzing the effect of peers on women's graduation outcomes. Panel A of Table 4 shows the effect of peer ability on graduation outcomes across all fields. The peer ability variables (average math rank of female and male peers) range from 0 to 1, so the reported coefficients represent the effect of moving from the least selective possible peers to the most selective possible peers. Having higher-ability female peers increases women's probability of graduating from any program and graduating on time by 7 p.p., driven entirely by increased STEM graduation. Higher-ability male peers show no significant effects in the overall sample.

Panel B confirms that these effects are concentrated among women who initially enrolled in STEM programs. For these women, having higher-ability female peers increases their probability of graduating from any program by 19 p.p. and their probability of graduating from STEM by 21 p.p. Examining the decomposition in Table 5 reveals the mechanisms behind these effects. Better female peers increase the probability of graduating from the initial program by 14 p.p. and reduce dropout rates by 11 p.p. The probability of switching fields remains largely unchanged, but among women who do switch, those with higher-ability female peers are more likely to transfer to another STEM program (where they are also more likely to graduate) rather than to non-STEM fields. As a result, the 21 p.p. increase in STEM graduation comes from two sources: 3 p.p. from women who would have otherwise graduated from non-STEM fields, and 19 p.p. from women who would have otherwise not graduated at all. To provide a more meaningful interpretation, we rescale our coefficients by 0.03, which represents a one standard deviation increase in peer ability. This rescaling is more appropriate than interpreting the raw coefficients, as in practice programs do not experience changes from the least to the most selective peers (i.e., from 0 to 1), but rather experience more moderate changes in peer composition over time. A one standard deviation increase in female peer ability increases women's probability of graduating from STEM by 1.3% ($0.21 \times 0.03/0.49$), their probability of graduating from the initial program by 1.2% ($0.14 \times 0.03/0.35$), and their probability of graduating from any field by 0.8% ($0.19 \times 0.03/0.69$).

The effects of higher-ability male peers on women in STEM are notably opposite in sign. These male peers significantly decrease women's probability of graduating from their initial STEM program and from STEM overall by 26 p.p. Table 5 reveals the mechanisms: women with higher-ability male peers experience higher dropout rates and are more likely to transfer out of their initial program. Among those who transfer, a substantial proportion moves to non-STEM fields, and these women are more likely to graduate from non-STEM programs (12 p.p.). The 26 p.p. decrease in STEM graduation is thus partially offset by an increase in non-STEM graduation, resulting in a negative but statistically insignificant effect on overall graduation. This pattern suggests that higher-ability male peers push some women out of STEM: some switch to non-STEM and eventually graduate, while others drop out entirely. In terms of magnitude, a one standard deviation increase in male peer ability decreases women's probability of graduating from STEM by 1.6% ($0.26 \times 0.03/0.49$) and their probability of graduating from the initial program by 2.3% ($0.26 \times 0.03/0.35$).

Panel C shows that for women in non-STEM programs, peer ability has no significant effects on any graduation outcome. Moreover, formal tests confirm that peer effects differ significantly across fields: we can reject equality of effects between STEM and non-STEM for female peers on university graduation and STEM graduation, and for male peers on STEM graduation. These results confirm that the most substantial peer effects on women's graduation outcomes are concentrated in STEM fields.

We now turn to men's graduation outcomes, where the patterns differ substantially from those observed for women. For men who initially enrolled in STEM programs (Panel B), peer ability shapes educational trajectories but has little impact on overall graduation rates. Better female peers increase the probability of graduating from the initial program by 10 p.p., though the effects on overall graduation are smaller and imprecise.

The results for male peers reveal a recomposition of trajectories. Higher-ability male peers reduce graduation from the initial STEM program and reduce direct dropout, generating a large increase in program switching of 22 p.p. Crucially, this reallocation does not push men out of STEM: some transfer to other STEM programs, leaving overall STEM graduation largely unchanged, while others move into non-STEM fields

Table 4
Female and male peer effects on graduation outcomes across STEM and non-STEM fields.

	Women					Men				
	Grad: Any (1)	Grad: On time (2)	Grad: STEM (3)	Grad: Non-STEM (4)	Grad: Program (5)	Grad: Any (6)	Grad: On time (7)	Grad: STEM (8)	Grad: Non-STEM (9)	Grad: Program (10)
Panel A: All										
Mean rank of female peers	0.07**	0.07*	0.07**	0.00	0.05	−0.00	−0.01	0.07**	−0.07***	0.00
	(0.04)	(0.04)	(0.03)	(0.04)	(0.05)	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)
Mean rank of male peers	−0.02	−0.01	0.01	−0.02	−0.06	0.02	0.02	0.02	−0.00	−0.07
	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.05)
Share of female peers	0.04***	0.04***	0.00	0.04**	0.06***	0.04**	0.04**	0.01	0.03*	0.06***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Mean dependent variable	0.76	0.73	0.12	0.64	0.55	0.63	0.59	0.26	0.38	0.41
N. Clus.	1365	1365	1365	1365	1365	1353	1353	1353	1353	1353
N. Obs.	259,333	259,333	259,333	259,333	259,333	279,203	279,203	279,203	279,203	279,203
Panel B: STEM										
Mean rank of female peers	0.19***	0.20***	0.21***	−0.03	0.14*	0.05	0.03	0.06	−0.01	0.10**
	(0.07)	(0.07)	(0.08)	(0.06)	(0.08)	(0.04)	(0.04)	(0.04)	(0.02)	(0.04)
Mean rank of male peers	−0.14	−0.14	−0.26***	0.12*	−0.26***	0.05	0.04	−0.03	0.08**	−0.11
	(0.09)	(0.09)	(0.09)	(0.07)	(0.10)	(0.07)	(0.07)	(0.07)	(0.04)	(0.08)
Share of female peers	0.09***	0.09***	0.06*	0.04	0.05	0.04*	0.03	0.03	0.02	0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
Mean dependent variable	0.69	0.59	0.49	0.21	0.35	0.60	0.52	0.51	0.10	0.31
N. Clus.	456	456	456	456	456	466	466	466	466	466
N. Obs.	58,720	58,720	58,720	58,720	58,720	138,080	138,080	138,080	138,080	138,080
Panel C: non-STEM										
Mean rank of female peers	0.05	0.05	0.02	0.03	0.03	−0.09*	−0.09*	0.03	−0.12**	−0.12**
	(0.04)	(0.04)	(0.02)	(0.04)	(0.05)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)
Mean rank of male peers	−0.01	0.00	0.01	−0.02	−0.04	0.03	0.03	0.00	0.03	−0.01
	(0.03)	(0.03)	(0.01)	(0.03)	(0.04)	(0.05)	(0.05)	(0.01)	(0.05)	(0.05)
Share of female peers	0.02	0.02	−0.01**	0.03*	0.05**	0.01	0.02	−0.01**	0.02	0.05*
	(0.02)	(0.02)	(0.00)	(0.02)	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)
Mean dependent variable	0.78	0.77	0.01	0.77	0.61	0.66	0.65	0.02	0.65	0.51
N. Clus.	908	908	908	908	908	887	887	887	887	887
N. Obs.	200,340	200,340	200,340	200,340	200,340	140,905	140,905	140,905	140,905	140,905

Notes: This table presents estimates of the effects of male and female peers' average math rank on students' graduation probabilities, observed 12 years after high school graduation. Panel A includes all programs, Panel B shows results for STEM programs, and Panel C shows results for non-STEM programs. For women (columns 1–5) and men (columns 6–10), we examine the probability of graduating from: any program, on-time graduation, graduation from a STEM program, graduation from a non-STEM program, and graduation from the initial program. All specifications include program fixed effects, major-by-cohort and university-by-cohort fixed effects, preference controls, and controls for individual characteristics. Standard errors clustered at the program level are shown in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

where they are more likely to graduate, increasing non-STEM graduation by 8 p.p. For women in STEM, by contrast, higher-ability male peers reduce STEM graduation and increase dropout, with a negative — though imprecise — net effect on overall graduation. The key difference lies in the nature of the reallocation: for men, switching leads to fields where they ultimately succeed, while for women it involves a larger dropout margin. Formal tests confirm that these gender differences are statistically significant.

For men in non-STEM programs, Panel C reveals a different pattern: higher-ability female peers have negative effects on men's outcomes. Better female peers decrease men's probability of graduating from their initial program by 12 p.p. Many of these men drop out entirely, which translates into a 9 p.p. decrease in the probability of graduating overall. This mirrors the pattern observed for women in STEM fields who face higher-ability male peers, though the effects for men are smaller in magnitude. In terms of standardized effects, a one standard deviation increase in female peer ability decreases men's probability of graduating from their initial non-STEM program by 0.7% ($0.12 \times 0.03/0.51$) and their probability of graduating overall by 0.4% ($0.09 \times 0.03/0.66$).

Beyond peer ability, sex composition itself also affects graduation outcomes, though in a more modest and universal way. Throughout our specifications, we control for the share of female students among peers to separate these two effects. A one standard deviation increase in female share (0.06) increases the probability of graduating from the initial program by approximately 0.3 p.p. (0.05×0.06) for both men and women. Unlike the large sex-specific ability effects concentrated in STEM, this sex composition effect operates similarly across both STEM and non-STEM fields.

Finally, to examine which parts of the peer ability distribution drive our results, we consider alternative measures in Table 6. Columns 1 and 7 pool all peers together, using the average rank of both male and female peers combined. This specification reveals limited significant effects, consistent with our main findings that male and female peer ability often operate in opposite directions, particularly for women in STEM, causing them to offset each other when pooled. Columns 2–3, 5–6, 8–9, and 11–12 utilize alternative measures based on the distribution of peer ability: the percentage of peers in the bottom versus top quartile of math performance. Although these specifications are noisier, they reveal an important pattern: peer effects operate through both ends of the ability distribution, not just from high-performing peers. For instance, in STEM (Panel B), women are both harmed by low-performing female peers and benefit from high-performing female peers, with opposite patterns for male peers. These findings support our use of average peer ability as our primary measure, as both ends of the distribution matter for outcomes.

6.2. *Effects of peer ability on labor market outcomes*

We next investigate how peer ability affects labor market outcomes. While our findings demonstrate that peer ability influences

Table 5
Female and male peer effects on program switching outcomes across STEM and non-STEM fields.

	Women									Men								
	No switch		Any switch	Switch to STEM			Switch to non-STEM			No switch		Any switch	Switch to STEM			Switch to non-STEM		
	Grad (1)	No grad (2)	Any field (3)	Any (4)	Grad (5)	No grad (6)	Any (7)	Grad (8)	No grad (9)	Grad (10)	No grad (11)	Any field (12)	Any (13)	Grad (14)	No grad (15)	Any (16)	Grad (17)	No grad (18)
Panel A: All																		
Mean rank of female peers	0.05	−0.05	−0.00	0.03	0.02	0.00	−0.03	−0.00	−0.03	0.00	0.00	−0.01	−0.01	−0.01	−0.01	0.01	0.00	0.00
	(0.05)	(0.03)	(0.04)	(0.02)	(0.02)	(0.01)	(0.04)	(0.03)	(0.02)	(0.04)	(0.03)	(0.04)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Mean rank of male peers	−0.06	0.01	0.05	0.03**	0.02	0.01	0.02	0.03	−0.01	−0.07	−0.06	0.13***	0.05	0.04*	0.01	0.08**	0.05*	0.03
	(0.04)	(0.03)	(0.04)	(0.02)	(0.01)	(0.01)	(0.03)	(0.03)	(0.02)	(0.05)	(0.04)	(0.04)	(0.03)	(0.02)	(0.02)	(0.04)	(0.03)	(0.02)
Share of female peers	0.06***	−0.04***	−0.02	−0.01	−0.01	−0.01	−0.00	−0.01	0.01	0.06***	−0.00	−0.06***	−0.04***	−0.02*	−0.02**	−0.02	−0.01	−0.01
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Mean dependent variable	0.55	0.15	0.30	0.06	0.04	0.02	0.24	0.17	0.07	0.41	0.20	0.39	0.19	0.11	0.08	0.20	0.12	0.08
N. Clus.	1365	1365	1365	1365	1365	1365	1365	1365	1365	1353	1353	1353	1353	1353	1353	1353	1353	1353
N. Obs.	259,333	259,333	259,333	259,333	259,333	259,333	259,333	259,333	259,333	279,203	279,203	279,203	279,203	279,203	279,203	279,203	279,203	279,203
Panel B: STEM																		
Mean rank of female peers	0.14*	−0.12*	−0.03	0.04	0.06	−0.03	−0.07	−0.02	−0.05	0.10**	−0.03	−0.07	−0.06	−0.04	−0.02	−0.01	−0.01	−0.00
	(0.08)	(0.07)	(0.09)	(0.07)	(0.05)	(0.04)	(0.07)	(0.06)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Mean rank of male peers	−0.26***	0.10	0.16	0.09	−0.00	0.10*	0.06	0.12*	−0.05	−0.11	−0.12*	0.22***	0.11	0.08	0.03	0.11**	0.08**	0.04
	(0.10)	(0.08)	(0.10)	(0.08)	(0.06)	(0.05)	(0.08)	(0.07)	(0.05)	(0.08)	(0.06)	(0.08)	(0.08)	(0.05)	(0.05)	(0.05)	(0.04)	(0.03)
Share of female peers	0.05	−0.10***	0.04	0.01	0.00	0.01	0.03	0.04	−0.00	0.04	−0.00	−0.04	−0.03	−0.02	−0.01	−0.01	0.02	−0.03**
	(0.03)	(0.03)	(0.04)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Mean dependent variable	0.35	0.16	0.49	0.22	0.14	0.08	0.27	0.20	0.07	0.31	0.21	0.49	0.34	0.20	0.14	0.15	0.10	0.05
N. Clus.	456	456	456	456	456	456	456	456	456	466	466	466	466	466	466	466	466	466
N. Obs.	58,720	58,720	58,720	58,720	58,720	58,720	58,720	58,720	58,720	138,080	138,080	138,080	138,080	138,080	138,080	138,080	138,080	138,080
Panel C: non-STEM																		
Mean rank of female peers	0.03	−0.03	−0.00	0.02	0.02	−0.00	−0.02	−0.00	−0.02	−0.12**	0.10**	0.01	0.01	0.03	−0.02	−0.00	−0.01	0.01
	(0.05)	(0.04)	(0.05)	(0.02)	(0.02)	(0.01)	(0.05)	(0.04)	(0.03)	(0.06)	(0.04)	(0.05)	(0.03)	(0.02)	(0.02)	(0.05)	(0.04)	(0.03)
Mean rank of male peers	−0.04	0.00	0.04	0.01	0.01	0.00	0.02	0.02	0.00	−0.01	−0.02	0.02	−0.01	0.00	−0.02	0.03	0.03	0.00
	(0.04)	(0.03)	(0.04)	(0.01)	(0.01)	(0.01)	(0.04)	(0.03)	(0.02)	(0.05)	(0.04)	(0.05)	(0.02)	(0.01)	(0.01)	(0.05)	(0.04)	(0.03)
Share of female peers	0.05**	−0.03*	−0.03	−0.02**	−0.01**	−0.01	−0.01	−0.02	0.01	0.05*	0.01	−0.05**	−0.03***	−0.01*	−0.02**	−0.03	−0.03	−0.00
	(0.03)	(0.02)	(0.02)	(0.01)	(0.00)	(0.00)	(0.02)	(0.02)	(0.01)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Mean dependent variable	0.61	0.14	0.25	0.02	0.01	0.01	0.23	0.16	0.07	0.51	0.20	0.29	0.04	0.02	0.03	0.24	0.14	0.11
N. Clus.	908	908	908	908	908	908	908	908	908	887	887	887	887	887	887	887	887	887
N. Obs.	200,340	200,340	200,340	200,340	200,340	200,340	200,340	200,340	200,340	140,905	140,905	140,905	140,905	140,905	140,905	140,905	140,905	140,905

Notes: This table presents estimates of the effects of male and female peers' average math rank on student trajectories after initial enrollment. Panel A includes all programs, Panel B shows results for STEM programs, and Panel C shows results for non-STEM programs. For women (columns 1–9) and men (columns 10–18), we examine whether students: remain in their initial program and graduate (column 1, 10), remain but do not graduate (column 2, 11), switch to any program (column 3, 12), switch to a STEM program (columns 4–6, 13–15), or switch to a non-STEM program (columns 7–9, 16–18). For switchers, we further distinguish whether they graduate or not from their destination field. All specifications include program fixed effects, major-by-cohort and university-by-cohort fixed effects, preference controls, and controls for individual characteristics. Standard errors clustered at the program level are shown in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.1$.

Table 6
Female and male peer effects using alternative ability measures.

	Women						Men					
	Grad: Any			Grad: Program			Grad: Any			Grad: Program		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: All												
Peer average ranks	0.05			−0.02			0.01			−0.10*		
	(0.05)			(0.06)			(0.05)			(0.06)		
% Female peers in bottom quartile		−0.02*			−0.03**			−0.00			−0.01	
		(0.01)			(0.01)			(0.01)			(0.01)	
% Male peers in bottom quartile		0.01			0.01			−0.00			0.00	
		(0.01)			(0.01)			(0.01)			(0.01)	
% Female peers in top quartile			−0.01			−0.01			−0.00			0.00
			(0.01)			(0.02)			(0.01)			(0.01)
% Male peers in top quartile			−0.00			−0.01			0.00			−0.02*
			(0.01)			(0.01)			(0.01)			(0.01)
Mean	0.76	0.76	0.76	0.56	0.55	0.55	0.63	0.63	0.63	0.41	0.41	0.41
N Clus	1385	1365	1365	1385	1365	1365	1366	1353	1353	1366	1353	1353
Obs	269,302	259,333	259,333	269,302	259,333	259,333	283,020	279,203	279,203	283,020	279,203	279,203
Panel B: STEM												
Peer average rank	0.10			−0.11			0.12*			0.04		
	(0.10)			(0.13)			(0.07)			(0.09)		
% Female peers in bottom quartile		−0.02			−0.04**			−0.00			−0.02	
		(0.02)			(0.02)			(0.01)			(0.01)	
% Male peers in bottom quartile		0.02			0.04			−0.01			0.01	
		(0.02)			(0.03)			(0.02)			(0.02)	
% Female peers in top quartile			0.03			0.02			0.02*			0.03**
			(0.02)			(0.02)			(0.01)			(0.01)
% Male peers in top quartile			−0.03			−0.03			−0.00			−0.03
			(0.02)			(0.03)			(0.02)			(0.02)
Mean	0.69	0.69	0.69	0.35	0.35	0.35	0.60	0.60	0.60	0.31	0.31	0.31
N Clus	460	456	456	460	456	456	469	466	466	469	466	466
Obs	58,859	58,720	58,720	58,859	58,720	58,720	140,124	138,080	138,080	140,124	138,080	138,080
Panel C: Non-STEM												
Peer average rank	0.04			0.00			−0.07			−0.14*		
	(0.05)			(0.07)			(0.06)			(0.07)		
% Female peers in bottom quartile		−0.02			−0.02			0.01			0.01	
		(0.01)			(0.02)			(0.01)			(0.02)	
% Male peers in bottom quartile		0.01			0.01			−0.00			−0.01	
		(0.01)			(0.02)			(0.01)			(0.02)	
% Female peers in top quartile			−0.02			−0.02			−0.04**			−0.04**
			(0.02)			(0.02)			(0.02)			(0.02)
% Male peers in top quartile			0.00			−0.01			0.01			−0.01
			(0.01)			(0.01)			(0.01)			(0.01)
Mean	0.78	0.78	0.78	0.61	0.61	0.61	0.66	0.66	0.66	0.51	0.51	0.51
N Clus	924	908	908	924	908	908	897	887	887	897	887	887
Obs	210,167	200,340	200,340	210,167	200,340	200,340	142,676	140,905	140,905	142,676	140,905	140,905

Notes: This table replicates the analysis from Table 5 using three alternative measures of peer ability: (1) the average peer math rank, (2) the percentage of male and female peers in the bottom quartile of the math rank distribution within their program, and (3) the percentage of male and female peers in the top quartile. Panel A includes all programs, Panel B shows results for STEM programs, and Panel C shows results for non-STEM programs. For women (columns 1–6) and men (columns 7–12), we examine graduation from any program and graduation from initial program. All specifications include program fixed effects, major-by-cohort and university-by-cohort fixed effects, preference controls, and controls for individual characteristics. Standard errors clustered at the program level are shown in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

students' educational trajectories — including graduation rates, timing, and program completion — how these effects translate into earnings is not straightforward. The relationship between educational outcomes and labor market success is complex. Students who leave their initial programs due to peer effects might switch into alternative fields with similar or even higher earnings potential, potentially offsetting negative effects on graduation. This is particularly relevant in our setting, as prior research finds that STEM degrees yield substantial earnings premiums for men but not for women in the Chilean labor market (Aguirre et al., 2025), suggesting that the consequences of switching out of STEM may differ by sex. Moreover, peers may influence labor market outcomes even without affecting graduation probabilities, either through their impact on unmeasured academic outcomes (such as GPA or program specialization) or through their lasting influence as professional networks and references (as discussed in Section 2).

Table 7 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, accumulated months of work experience during years 8–10 after enrollment, and the number of employers during this same period. At this point (10 years after high school), approximately 59% of women and 63% of men in our sample are employed in the private sector. Conditional on having worked at least one month, women's annual earnings are \$14,900 and men's are \$16,519. During years 8–10 after enrollment, women have accumulated an average of 15.6 months of work experience and had 2.3 different employers, while men have 16.1 months of experience and 2.5 employers.

We find that peer ability effects on labor market outcomes are concentrated among women in STEM fields. For these women, higher-ability male peers negatively affect employment and earnings, consistent with the detrimental effects on STEM graduation documented earlier. These results suggest that the negative impact of male peers on women's educational outcomes translates directly into reduced labor market success. In contrast, while female peers had strong positive

Table 7
Female and male peer effects on labor market outcomes across STEM and non-STEM fields.

	Women					Men				
	Employed (1)	Annual earnings (2)	Annual earnings if employed (3)	Months of experience (4)	Number of employers (5)	Employed (6)	Annual earnings (7)	Annual earnings if employed (8)	Months of experience (9)	Number of employers (10)
Panel A: All										
Mean rank of female peers	0.04	79.52	−876.2	−1.06	−0.11	0.00	−208.0	−1023	0.09	−0.13
	(0.05)	(1198)	(1411)	(1.49)	(0.22)	(0.04)	(1122)	(1174)	(1.21)	(0.19)
Mean rank of male peers	−0.07*	−2163***	−1006	−2.04*	−0.27	−0.02	147.7	663.4	−1.44	−0.26
	(0.04)	(794.0)	(894.6)	(1.13)	(0.17)	(0.05)	(1108)	(1287)	(1.39)	(0.23)
Share of female peers	0.00	−110.6	−335.6	0.71	0.04	0.04**	149.3	−984.9	1.13**	0.10
	(0.02)	(428.7)	(562.4)	(0.56)	(0.09)	(0.02)	(543.1)	(652.0)	(0.56)	(0.08)
Mean dependent variable	0.59	8795	14,900	15.59	2.32	0.63	10,407	16,519	16.10	2.46
N. Clus.	954	954	946	954	954	946	946	940	946	946
N. Obs.	170,931	170,931	100,860	170,931	170,931	187,712	187,712	118,237	187,712	187,712
Panel B: STEM										
Mean rank of female peers	0.04	922.6	873.8	−1.81	−0.14	0.06	253.2	−1113	0.72	−0.03
	(0.09)	(2293)	(2932)	(2.78)	(0.40)	(0.05)	(1704)	(1599)	(1.66)	(0.25)
Mean rank of male peers	−0.21*	−5732**	−4059	−5.52*	−0.60	−0.02	−1575	−996.8	−0.20	−0.09
	(0.11)	(2609)	(3397)	(3.12)	(0.47)	(0.07)	(2109)	(2478)	(2.32)	(0.38)
Share of female peers	−0.04	−1416*	−979.4	−0.99	−0.19	0.03	−842.0	−1969**	−0.11	−0.09
	(0.04)	(845.7)	(1149)	(1.12)	(0.17)	(0.03)	(866.0)	(997.5)	(0.83)	(0.12)
Mean dependent variable	0.62	9798	15,735	15.63	2.39	0.69	12,595	18,277	17.61	2.66
N. Clus.	348	348	340	348	348	352	352	352	352	352
N. Obs.	40,852	40,852	25,329	40,852	40,852	94,158	94,158	64,842	94,158	94,158
Panel C: non-STEM										
Mean rank of female peers	0.01	−837.9	−2064	−1.34	−0.21	−0.09	−1886	−2175	−0.98	−0.23
	(0.06)	(1424)	(1611)	(1.80)	(0.26)	(0.07)	(1323)	(1724)	(1.94)	(0.31)
Mean rank of male peers	−0.06	−1726**	−455.3	−1.48	−0.20	−0.01	874.9	1428	−1.07	−0.21
	(0.04)	(827.5)	(893.9)	(1.24)	(0.19)	(0.06)	(1279)	(1529)	(1.85)	(0.31)
Share of female peers	0.02	490.8	101.1	1.16*	0.12	0.04	908.5	−45.14	1.66**	0.17
	(0.02)	(494.5)	(662.4)	(0.68)	(0.11)	(0.03)	(585.4)	(726.4)	(0.75)	(0.11)
Mean dependent variable	0.58	8481	14,623	15.57	2.30	0.57	8204	14,389	14.58	2.26
N. Clus.	606	606	606	606	606	594	594	588	594	594
N. Obs.	129,951	129,951	75,322	129,951	129,951	93,427	93,427	53,224	93,427	93,427

Notes: This table presents estimates of the effects of male and female peers' average math rank on students' labor market outcomes 10 years after high school graduation. Panel A includes all programs, Panel B shows results for STEM programs, and Panel C shows results for non-STEM programs. For women (columns 1–5) and men (columns 6–10), we examine: employment probability, annual earnings (including zeros), annual earnings if employed, accumulated months of work experience, and total number of employers. All specifications include program fixed effects, major-by-cohort and university-by-cohort fixed effects, preference controls, and controls for individual characteristics. Standard errors clustered at the program level are shown in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

effects on women's STEM graduation, the estimated effects on labor market outcomes are positive but not statistically significant. Outside of women in STEM, peer ability shows limited effects on labor market outcomes. For women in non-STEM fields, while there is some evidence that higher-ability male peers decrease earnings, these effects are smaller in magnitude than those observed in STEM. For men, peer ability shows no significant effects on labor market outcomes, consistent with the limited effects observed for graduation.

We begin by examining women's labor market outcomes. Panel A of Table 7 presents findings across all fields. Higher-ability male peers negatively impact multiple dimensions of women's labor market outcomes, decreasing employment probability by 7 p.p., annual earnings by \$2163, and accumulated work experience by 2 months. In contrast, higher-ability female peers show no significant effects on women's employment, earnings, or work experience. Panel B confirms that these effects are most pronounced among women who initially enrolled in STEM programs. Higher-ability male peers reduce women's employment probability by 21 p.p., annual earnings by \$5732, and accumulated work experience by 5.5 months. A one standard deviation increase in male peer ability decreases women's probability of being employed by 1.0% ($0.21 \times 0.03/0.62$), their earnings by 1.7% ($0.21 \times 0.03 \times 5732/9798$), and their work experience by 1.1% ($0.21 \times 0.03 \times 5.52/15.63$). These findings mirror our graduation results, where higher-ability male peers reduced women's STEM graduation rates 1.6%. The consistency across educational and labor market outcomes suggests that male peers' negative effects persist beyond college, affecting women's long-term career trajectories. In contrast, the effects of female peers on women in STEM show a different pattern: while female peers had strong positive effects on STEM graduation (increasing graduation rates by 1.3% per standard deviation), the estimated effects on labor market outcomes are positive but not statistically significant. This suggests that the educational benefits of female peers may not fully translate into measurable earnings gains, at least within the timeframe we observe.

Panel C shows that higher-ability male peers also negatively affect women's earnings in non-STEM fields, reducing annual earnings by \$1726. This effect is considerably smaller than in STEM and represents a different pattern from our graduation results: male peers did not significantly affect women's graduation outcomes in non-STEM fields, suggesting they may influence education quality or professional networks without changing graduation rates. Higher-ability female peers show no significant effects on employment or earnings in non-STEM fields.

For men, peer ability shows no significant effects on labor market outcomes across both STEM and non-STEM fields, consistent with the limited effects observed for graduation. While higher-ability female peers reduced men's graduation rates in non-STEM programs by 0.4% per standard deviation, these educational effects do not translate into significant earnings effects. This pattern reinforces that peer ability

Table 8
Female and male peer effects on fertility outcomes across STEM and non-STEM fields.

	Women		Men	
	Has child (1)	Number of children (2)	Has Child (3)	Number of children (4)
Panel A: All				
Mean rank of female peers	−0.14***	−0.21***	−0.03	−0.05
	(0.04)	(0.07)	(0.03)	(0.05)
Mean rank of male peers	0.03	0.01	−0.03	−0.03
	(0.04)	(0.05)	(0.04)	(0.06)
Share of female peers	−0.02	−0.02	−0.01	−0.01
	(0.02)	(0.02)	(0.02)	(0.02)
Mean dependent variable	0.29	0.39	0.23	0.31
N. Clus.	954	954	946	946
N. Obs.	170,931	170,931	187,712	187,712
Panel B: STEM				
Mean rank of female peers	−0.22**	−0.32**	−0.04	−0.07
	(0.09)	(0.13)	(0.05)	(0.06)
Mean rank of male peers	0.04	−0.01	0.05	0.09
	(0.11)	(0.15)	(0.08)	(0.11)
Share of female peers	−0.08**	−0.11**	−0.03	−0.04
	(0.03)	(0.05)	(0.03)	(0.04)
Mean dependent variable	0.27	0.37	0.23	0.31
N. Clus.	348	348	352	352
N. Obs.	40,852	40,852	94,158	94,158
Panel C: non-STEM				
Mean rank of female peers	−0.13**	−0.20**	−0.00	0.05
	(0.05)	(0.08)	(0.05)	(0.07)
Mean rank of male peers	0.02	0.01	−0.07	−0.09
	(0.04)	(0.06)	(0.05)	(0.08)
Share of female peers	0.00	0.01	−0.00	0.01
	(0.02)	(0.03)	(0.02)	(0.03)
Mean dependent variable	0.29	0.40	0.23	0.31
N. Clus.	606	606	594	594
N. Obs.	129,951	129,951	93,427	93,427

Notes: This table presents estimates of the effects of male and female peers' average math rank on students' fertility outcomes 11 years after high school graduation. Panel A includes all programs, Panel B shows results for STEM programs, and Panel C shows results for non-STEM programs. For women (columns 1–2) and men (columns 3–4), we examine: having at least one child and total number of children. All specifications include program fixed effects, major-by-cohort and university-by-cohort fixed effects, preference controls, and controls for individual characteristics. Standard errors clustered at the program level are shown in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

plays a considerably less important role in shaping men's outcomes compared to women in STEM.

Beyond peer ability, the share of female students among peers also affects labor market outcomes, though these effects differ from those observed for graduation. In our graduation analysis, a higher share of female students had modest positive effects on persistence. However, we find no significant positive effects on earnings, and in STEM fields we observe negative effects on earnings for both women and men. Here too, these sex composition effects are considerably smaller in magnitude than the sex-specific peer ability effects documented above.

One limitation of our earnings analysis is that it excludes public sector employees and self-employed workers. While we lack public sector employment data for most of our study period, we have access to data for 2019. Appendix Table A.7 shows that 19% of women and 12% of men in our sample are employed in the public sector. Analysis of this 2019 data reveals that, consistent with our main findings for women in STEM, higher-ability male peers significantly decrease both their probability of public sector employment (by 16 p.p.) and their public sector earnings (by \$4234). Higher-ability female peers show positive but statistically insignificant effects on women's public sector outcomes in STEM. These findings suggest that our inability to observe public sector earnings throughout the study period likely leads us to underestimate the true magnitude of peer effects on earnings for women in STEM programs, particularly the negative effects of high-achieving male peers. Because we lack panel data on public sector earnings, this comparison of individuals across different cohorts and ages necessitates stronger identification assumptions than our main regression. However, it is encouraging that the observed effects operate in the same direction.

6.3. Effects of peer ability on fertility and marriage

Finally, we examine the effect of peer ability on fertility and marriage outcomes. In Table 8, we present estimates of the impact of male and female peers' average math rank on fertility outcomes 11 years after high school graduation. In our sample, 29% of women and 23% of men have had a child by this point.

Panel A shows that higher-ability female peers significantly decrease fertility outcomes for women across all fields. A one standard deviation increase in female peer ability reduces the probability of having a child by 1.4% ($0.14 \times 0.03/0.29$) and decreases the number of children by 1.6% ($0.21 \times 0.03/0.39$).

Panels B and C reveal that the effects of female peers on women's fertility appear in both STEM and non-STEM programs, though the point estimates are larger in STEM. In STEM, a one standard deviation increase in female peer ability reduces the probability of having a child by 2.4% ($0.22 \times 0.03/0.27$) and decreases the number of

Table 9
Female and male peer effects on marriage outcomes across STEM and non-STEM fields.

	Women								Men							
	Married	Has partner	Has partner w/data	Partner from same program	Partner GPA rank	Partner language rank	Partner math rank	Partner annual earnings	Married	Has partner	Has partner w/data	Partner from same program	Partner GPA rank	Partner language rank	Partner math rank	Partner annual earnings
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: All																
Mean rank of female peers	−0.05	−0.13***	−0.07*	−0.05	0.14**	0.10*	0.14**	3534	−0.00	−0.05	−0.04	0.05	0.07	0.11**	0.13***	2394
	(0.03)	(0.04)	(0.04)	(0.07)	(0.06)	(0.06)	(0.06)	(2807)	(0.02)	(0.04)	(0.03)	(0.05)	(0.05)	(0.04)	(0.05)	(1584)
Mean rank of male peers	−0.00	0.03	−0.01	0.01	−0.03	0.04	0.02	−1457	0.01	−0.02	−0.05	−0.09	−0.02	−0.01	−0.02	979.1
	(0.03)	(0.04)	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)	(2150)	(0.03)	(0.04)	(0.04)	(0.07)	(0.06)	(0.06)	(0.06)	(1869)
Share of female peers	−0.01	−0.01	−0.01	−0.24***	−0.04*	−0.07***	−0.07***	−441.1	−0.00	−0.01	0.00	0.10***	−0.03	0.00	0.00	750.2
	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(1309)	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(812.5)
Mean dependent variable	0.15	0.33	0.21	0.14	0.55	0.60	0.64	13,458.30	0.11	0.25	0.20	0.12	0.62	0.58	0.56	7171.64
N. Clus.	954	954	954	930	925	925	924	930	946	946	946	926	915	916	916	926
N. Obs.	170,931	170,931	170,931	35,460	31,722	31,795	31,796	35,460	187,712	187,712	187,712	37,963	32,566	32,613	32,605	37,963
Panel B: STEM																
Mean rank of female peers	−0.09	−0.27***	−0.15*	−0.01	0.05	0.00	0.13	50.46	0.01	−0.05	−0.03	0.06	0.01	0.13**	0.14**	2284
	(0.07)	(0.09)	(0.08)	(0.22)	(0.18)	(0.16)	(0.15)	(8308)	(0.03)	(0.05)	(0.05)	(0.05)	(0.07)	(0.06)	(0.06)	(2301)
Mean rank of male peers	0.04	0.13	0.16*	0.15	0.16	0.67***	0.49***	−1146	0.02	0.10	0.02	−0.05	0.23**	0.02	0.04	−1059
	(0.08)	(0.11)	(0.10)	(0.24)	(0.21)	(0.19)	(0.18)	(9715)	(0.05)	(0.08)	(0.07)	(0.10)	(0.11)	(0.11)	(0.10)	(3624)
Share of female peers	−0.01	−0.04	−0.02	−0.25***	−0.05	−0.09	−0.02	−134.0	−0.02	−0.05*	−0.03	0.12***	0.01	0.02	−0.00	1474
	(0.03)	(0.03)	(0.03)	(0.09)	(0.06)	(0.06)	(0.06)	(3641)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(1445)
Mean dependent variable	0.14	0.31	0.20	0.17	0.55	0.59	0.66	14,728.27	0.10	0.26	0.20	0.07	0.60	0.56	0.55	7043.73
N. Clus.	348	348	348	318	316	316	316	318	352	352	352	348	344	344	344	348
N. Obs.	40,852	40,852	40,852	7575	6671	6677	6678	7575	94,158	94,158	94,158	18,717	15,777	15,806	15,802	18,717
Panel C: non-STEM																
Mean rank of female peers	−0.05	−0.11**	−0.06	−0.01	0.09	0.12	0.08	1417	−0.02	−0.03	−0.05	0.12	0.13	0.08	0.12	2130
	(0.04)	(0.05)	(0.05)	(0.09)	(0.08)	(0.07)	(0.07)	(3366)	(0.04)	(0.06)	(0.05)	(0.11)	(0.09)	(0.08)	(0.09)	(2866)
Mean rank of male peers	−0.00	0.01	−0.03	0.02	−0.03	0.01	0.01	−1290	0.02	−0.05	−0.07	−0.16	−0.15*	−0.03	−0.03	1907
	(0.03)	(0.04)	(0.03)	(0.05)	(0.05)	(0.06)	(0.05)	(2338)	(0.04)	(0.05)	(0.05)	(0.11)	(0.09)	(0.08)	(0.08)	(2505)
Share of female peers	0.00	0.01	−0.00	−0.22***	−0.02	−0.05*	−0.08***	−221.9	−0.00	0.00	0.01	0.12***	−0.08**	0.04	0.01	252.7
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(1562)	(0.01)	(0.02)	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)	(1118)
Mean dependent variable	0.16	0.34	0.21	0.13	0.55	0.61	0.64	13,127.18	0.11	0.25	0.20	0.18	0.64	0.61	0.57	7323.35
N. Clus.	606	606	606	603	601	601	601	603	594	594	594	577	570	571	571	577
N. Obs.	129,951	129,951	129,951	27,365	24,479	24,543	24,546	27,365	93,427	93,427	93,427	18,892	16,377	16,394	16,390	18,892

Notes: This table presents estimates of the effects of male and female peers' average math rank on students' marriage market outcomes 10 years after high school graduation. Panel A includes all programs, Panel B shows results for STEM programs, and Panel C shows results for non-STEM programs. For women (columns 1–8) and men (columns 9–16), we examine: being married, having a partner (married or having a child together), having a partner with available academic and labor market data, having a partner from the same program, and partner characteristics (GPA rank, language rank, math rank, and annual earnings). All specifications include program fixed effects, major-by-cohort and university-by-cohort fixed effects, preference controls, and controls for individual characteristics. Standard errors clustered at the program level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10
Female and male peer effects by program sex composition.

	Women				Men			
	Grad: Any (1)	Grad: Program (2)	Annual earnings (3)	Has child (4)	Grad: Any (5)	Grad: Program (6)	Annual earnings (7)	Has child (8)
Panel A: STEM								
Mean rank of female peers	0.19**	0.02	−394.9	−0.25**	0.13	0.15	3340	0.09
	(0.08)	(0.10)	(2582)	(0.11)	(0.08)	(0.09)	(2658)	(0.10)
Mean rank of female peers × male share	−0.19	0.79**	11,068	0.43	−0.26	−0.16	−9665	−0.40
	(0.33)	(0.39)	(11,030)	(0.45)	(0.24)	(0.26)	(8701)	(0.28)
Mean rank of male peers	−0.16*	−0.24**	−5264**	0.08	0.03	−0.17*	−2727	−0.03
	(0.09)	(0.10)	(2572)	(0.11)	(0.09)	(0.09)	(2594)	(0.11)
Mean rank of male peers × male share	0.94**	1.09**	11,599	−1.52***	0.01	0.37	2935	0.31
	(0.47)	(0.52)	(15,900)	(0.55)	(0.31)	(0.39)	(10,946)	(0.37)
Mean dependent variable	0.7	0.4	9798	0.3	0.6	0.3	12,595	0.2
N. Clus	456	456	348	348	466	466	352	352
N. Obs	58,720	58,720	40,852	40,852	138,080	138,080	94,158	94,158
Panel B: Non-STEM								
Mean rank of female peers	0.04	0.02	1885	−0.08	−0.10**	−0.12**	−2053	0.00
	(0.05)	(0.06)	(1593)	(0.06)	(0.05)	(0.06)	(1316)	(0.05)
Mean rank of female peers × male share	0.04	−0.01	26,112***	0.28	0.13	0.33	−1727	0.32
	(0.23)	(0.32)	(6410)	(0.28)	(0.30)	(0.37)	(8154)	(0.34)
Mean rank of male peers	0.03	0.03	−1787	−0.04	0.06	0.02	1285	−0.09
	(0.06)	(0.07)	(1520)	(0.06)	(0.05)	(0.06)	(1447)	(0.06)
Mean rank of male peers × male share	0.15	0.27	−1500	−0.28	0.28	0.27	5234	−0.32
	(0.17)	(0.22)	(5024)	(0.21)	(0.29)	(0.30)	(7784)	(0.29)
Mean dependent variable	0.8	0.6	8481	0.3	0.7	0.5	8204	0.2
N. Clus	908	908	606	606	887	887	594	594
N. Obs	200,340	200,340	129,951	129,951	140,905	140,905	93,427	93,427

Notes: This table examines how the effects of peer ability vary with the sex composition of programs. For each program, we calculate the male share (proportion of male students) and re-center it at 0.5. We then estimate specifications that interact the mean rank of female and male peers with this re-centered male share. Panel A shows results for STEM programs and Panel B for non-STEM programs. The outcome variables include graduation from any program, graduation from initial program, annual earnings, and having at least one child. Main coefficients represent peer effects in sex-balanced programs (50% male). Interaction terms capture how these effects change as programs become more male-dominated. All specifications include program fixed effects, major-by-cohort and university-by-cohort fixed effects, preference controls, and controls for individual characteristics. Standard errors clustered at the program level are shown in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

children by 2.6% (0.32 × 0.03/0.37). In non-STEM, a one standard deviation increase reduces the probability of having a child by 1.3% (0.13 × 0.03/0.29) and decreases the number of children by 1.5% (0.20 × 0.03/0.40). Although we cannot statistically reject that these effects are equal across fields, the larger point estimates in STEM suggest potentially stronger effects in these programs.

These results are consistent with exposure to high-achieving female peers encouraging career focus and delaying childbearing among women. They align with our previous findings that female peers foster women's graduation outcomes. However, unlike our graduation results — where the positive effects of female peers were concentrated in STEM — the fertility effects appear across both STEM and non-STEM fields. Notably, male peers show no significant effects on fertility outcomes for women in either field, and peer ability shows no effects on men's fertility outcomes.

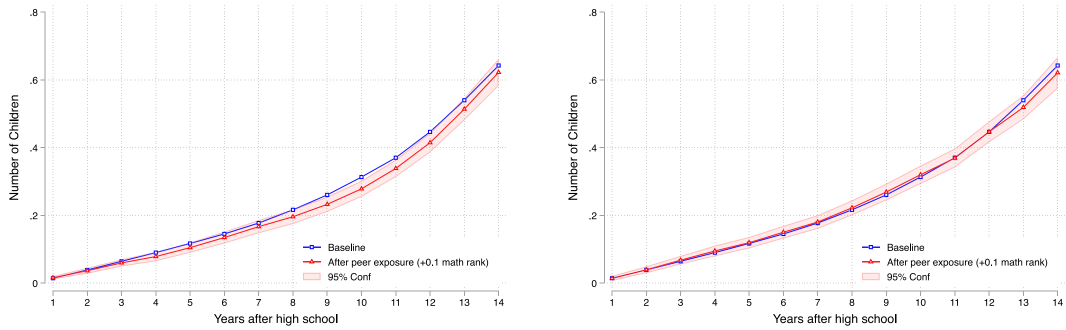
Beyond peer ability, the share of female students among peers also affects fertility outcomes. In STEM fields specifically, a one standard deviation increase in female share (0.06) reduces women's probability of having a child by 1.8% (0.08 × 0.06/0.27) and the number of children by 1.8% (0.11 × 0.06/0.37). We observe no significant effects of female share on fertility in non-STEM fields or for men. Here too, sex composition effects are smaller than the sex-specific peer ability effects documented above.

Fig. 3 illustrates how peer effects on fertility evolve over time for men and women in STEM fields. The blue line shows the baseline number of children at each age, while the red line indicates the probability for individuals exposed to peers with 0.1 higher average math rank. We estimate these coefficients using our baseline specification for number of children across different ages. While our dataset tracks all individuals through 11 years post-high school, we can only observe outcomes up to 14 years for pre-2004 high school cohorts, which results in decreased precision for longer-term estimates.

Women exposed to high-achieving female peers consistently show lower fertility rates throughout the observation period. By age 32 (14 years after high school), individuals in our sample have an average of 0.64 children. The negative effect of higher-ability female peers remains substantial and relatively stable over time, though it moderates slightly in later years. This pattern is consistent with women initially delaying childbearing and some eventually having children, though a meaningful gap in total fertility persists. In contrast, exposure to high-achieving male peers shows no significant effects on women's fertility. We find no significant effects of peer achievement on men's fertility decisions across any age group in our sample.

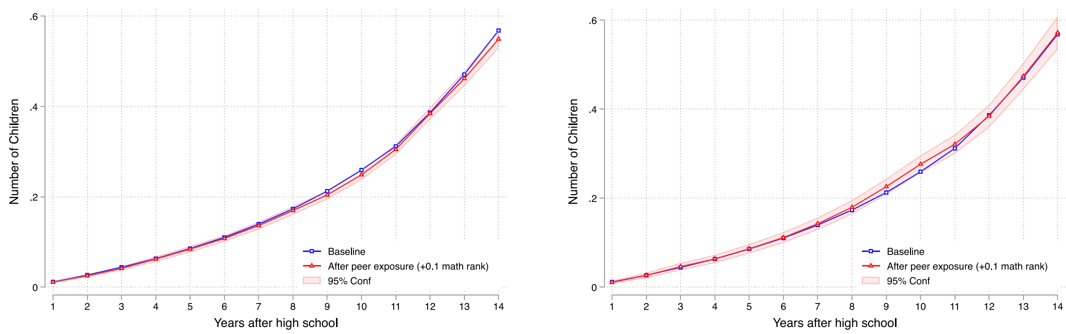
Moving on to Table 9, we investigate the impact of peer ability on marriage and partner characteristics 10 years after high school graduation, when subjects are approximately 28 years old.[23] We define a partner as either a spouse (if married) or the co-parent of a child (if unmarried with children). A decade post-graduation, 15% of women and 11% of men in our sample are married, while 33% of women and 25% of men have a partner by our definition. Data limitations restrict partner information (earnings, test scores, enrollment) to individuals who registered for the standardized admission test in or after 1999. Columns 3 and 11 indicate that partner data is available for approximately 21% of women and 20% of men.

[23] While we can observe fertility and marriage outcomes up to 11 years after high school graduation, we can only see partners' earnings 10 years after graduation, which is why we focus on this time frame for all outcomes.



High-achieving female peers High-achieving male peers

(a) Women



High-achieving female peers High-achieving male peers

(b) Men

Fig. 3. Female and male peer effects on fertility outcomes over time in STEM.
Notes: This figure shows the effect of exposure to higher-achieving peers on fertility over time for men and women in STEM programs. 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 male peers (right panels) or female peers (left panels) whose average math rank is 0.1 higher. Coefficients are estimated using our main specification with program fixed effects, major-by-cohort and university-by-cohort fixed effects, preference controls, and individual controls. Our sample allows us to observe all individuals up to 11 years after high school graduation, but we can only observe outcomes up to 14 years after high school graduation for individuals who completed high school before 2004.

Standard marriage market theory would predict that higher-ability same-sex peers increase competition for partners, while higher-ability opposite-sex peers expand access to high-ability potential partners. Our results provide no support for the competition hypothesis but are broadly consistent with the network expansion hypothesis—opposite-sex peers are associated with higher partner quality. Consistent with our findings for graduation and labor market outcomes, these patterns are particularly pronounced for women in STEM fields.

For men, Panel A shows that higher-ability female peers are associated with partners who have higher math and language test scores. A one standard deviation increase in female peer ability is associated with partners' math scores increasing by 0.7% ($0.13 \times 0.03/0.56$) and language scores by 0.6% ($0.11 \times 0.03/0.58$). Panels B and C show that these patterns appear in both STEM and non-STEM fields, with similar point estimates but greater precision in STEM. In contrast, male peers show no significant effects on men's partner characteristics, providing no evidence for the prediction that same-sex peers create competition in the marriage market.

The analysis for women is more complex because, as documented earlier, peer ability affects women's probability of having children and therefore the probability of observing a partner. This compositional effect makes it difficult to interpret effects on partner characteristics causally. Panel A shows that higher-ability female peers significantly decrease the probability of having a partner (by 13 p.p.) and the probability of having a partner with data (by 7 p.p.), while male peers increase the probability of observing a partner with data, though this effect is not statistically significant.

With this caveat in mind, we again find no evidence of competition effects from same-sex peers. More importantly, we find that opposite-sex peer ability improves partner ability for women in STEM fields. Panel B shows that a one standard deviation increase in male peer ability is associated with partners' language scores increasing by 2.2% ($0.49 \times 0.03/0.66$) and math scores by 3.7% ($0.67 \times 0.03/0.55$).

Beyond peer ability, the share of female students affects partner characteristics in intuitive ways. A higher female share significantly increases the probability that men partner with someone from the same program ($0.10 \times 0.06/0.12 = 5.0\%$ increase per standard deviation) while decreasing this probability for women ($-0.24 \times 0.06/0.14 = -10.3\%$ per standard deviation). Conditional on program fixed effects, cohorts with relatively more female students provide men with greater opportunities to meet female classmates as potential partners, while women face a relatively smaller pool of male classmates.

6.4. Field content versus gender environment within STEM

The analysis so far documents sizeable peer-ability effects, particularly for women in STEM programs. A central question, however, is whether these effects reflect features intrinsic to STEM content (e.g., curricula, grading practices, academic culture) or whether they arise from being in a male-dominated environment regardless of field. This section disentangles these forces by asking two related questions.

First, do peer-ability effects emerge in male-dominated programs regardless of whether they are STEM or non-STEM, consistent with a sex-environment explanation? Second, within STEM, do these effects vary systematically with the program's male share, consistent with an interaction between field content and sex composition?

To address these questions, we estimate a specification that allows the effect of peer ability to vary with the program's historical sex composition. For each program, we compute the share of men, $MaleShare_p$, and re-center it at 0.5 so that $\widetilde{MaleShare}_p \equiv MaleShare_p - 0.5$. We then interact the average ability of female peers and male peers with $\widetilde{MaleShare}_p$. Table 10 reports results separately by student sex and by field (Panel A: STEM; Panel B: non-STEM). Because the male-share variable is centered at 0.5, the main coefficients on female peers' and male peers' average ability can be interpreted as the peer-ability effects in a program with a balanced sex composition (50% men). The interaction terms capture how these effects change as the program becomes more male dominated. Specifically, moving from a sex-balanced program to a highly male-dominated one increases $\widetilde{MaleShare}_p$, so a positive (negative) interaction indicates that the peer effect becomes stronger (weaker) in more male-dominated environments.

Across the full sample, we identify 517 STEM programs, with an average male share of 0.68. Importantly, however, 109 STEM programs have less than 50% male enrollment, revealing some heterogeneity within STEM. These sex-balanced or female-majority STEM programs are overwhelmingly concentrated in life sciences and applied natural sciences, including biology, biochemistry, biotechnology, environmental sciences, marine sciences, food engineering, chemistry-related programs, and interdisciplinary science bachelor tracks.

Non-STEM programs also display variation in sex composition. Among the 977 non-STEM programs in our sample, 308 have a male share above 50%, and can therefore be classified as male-dominated. These programs are highly heterogeneous in terms of academic content and are drawn from a wide range of fields, including business and economics, law, social sciences, humanities, arts, architecture, agriculture, health-related programs, and teacher education. In contrast to male-dominated STEM programs, these non-STEM male-dominated fields do not share a common technical or quantitatively intensive core, nor are they historically associated with a single, well-defined male-typed academic identity.

The results for women highlight a sharp interaction between field and sex environment. In STEM programs with roughly balanced sex composition, we do not detect a positive effect of female peers' ability on women's outcomes. However, the interaction between female peers' ability and $\widetilde{MaleShare}_p$ is positive in STEM, implying that the effect of female peers becomes increasingly beneficial as the program becomes more male dominated. Consistent with this pattern, in highly male-dominated STEM programs the implied effect of high-ability female peers on women's graduation and subsequent outcomes is positive, whereas in sex-balanced STEM programs it is close to zero. In contrast, we find no evidence of a beneficial effect of female peers' ability for women in non-STEM programs: both the baseline effect at a balanced sex composition and its interaction with the male share are small, indicating that increasing the share of men does not generate the same positive role for high-ability female peers outside STEM. This pattern is consistent with a stereotype threat mechanism, as discussed in Section 2: gender stereotypes about quantitative ability are particularly salient in male-dominated STEM environments, where women are minorities in a technically demanding field historically associated with male competence. High-ability female peers may be especially valuable in this context as counterstereotypical role models that help women resist these pressures and persist in the field.

We find a different pattern for male peers. In STEM programs with balanced sex composition, male peers' ability has a negative effect on women's outcomes. Interestingly, this negative effect does not intensify in more male-dominated STEM programs: the interaction with $\widetilde{MaleShare}_p$ offsets the baseline effect, so that in highly male-dominated STEM programs the implied effect of male peers' ability is close to zero. Outside STEM, we again find no systematic effects of male peers' ability on women. Taken together, these results suggest that peer-ability effects are not driven solely by field content nor solely by sex composition in isolation. Instead, sex composition matters precisely within STEM: the benefits from high-ability female peers emerge only in highly male-dominated STEM programs, and the adverse effects from high-ability male peers are concentrated in more sex-balanced STEM programs, with neither pattern present in non-STEM fields.

6.5. Alternative peer characteristics

Our main analysis focuses on peer ability as the key dimension of the peer environment. We now examine whether other peer characteristics — specifically, peers' socioeconomic background — also affect outcomes. Appendix Tables A.7 and A.8 replace peer ability with peer socioeconomic characteristics (the share of male and female peers from private high schools and with tertiary-educated mothers) in our main specification. We find limited and inconsistent effects with substantially smaller magnitudes than our main peer ability results. This reinforces that peer ability — particularly distinguishing between male and female peer ability — is the most salient dimension of the peer environment for women in STEM.

7. Conclusion

Women remain significantly underrepresented in STEM fields across most countries, with important economic and social consequences. This paper examines whether the peer environment women face in college contributes to this gap. Using administrative data from Chile covering 33 universities and over 100 college majors, we exploit variation in peer composition across cohorts within programs to identify causal effects of peer ability on long-term outcomes including graduation, labor market performance, fertility, and marriage.

Our results reveal substantial peer ability effects specific to women in STEM fields. Higher-ability female peers increase women's probability of graduating from STEM programs, while higher-ability male peers substantially reduce their graduation rates, employment, and earnings. These peer ability effects are concentrated in STEM—we find no comparable effects for women in non-STEM fields or for men in any field. While our specifications control for the share of female peers and find modest positive effects on some outcomes, the effects of peer ability are substantially larger in magnitude.

These findings have important implications for policy, though we emphasize that our analysis identifies peer ability effects without definitively establishing the mechanisms behind them. First, interventions that increase women's exposure to high-achieving female peers in STEM could improve their persistence and success. Universities could structure laboratory sections, study groups, or first-year seminars to ensure women have meaningful contact with high-achieving female classmates who can serve as both academic partners and role models. Second, our findings indicate that the peer environment created by high-achieving male peers in STEM negatively affects women's outcomes. While we cannot determine whether this operates through competitive pressures, stereotype threat, shifts in classroom dynamics, or other channels, our results suggest that universities should pay attention to peer dynamics in STEM classrooms and consider whether pedagogical approaches, classroom structures, or support systems might mitigate these patterns. Understanding the underlying mechanisms would be valuable for designing more targeted interventions.

From a methodological perspective, our paper demonstrates the value of distinguishing between the ability of male and female peers in sex-segregated environments. Much existing literature focuses on peer sex composition, but our results show that peer ability composition may be equally or more important for understanding women's outcomes in STEM fields. As universities seek to increase women's representation and success in STEM, attention to peer dynamics and strategic composition of student cohorts may represent an important avenue for intervention.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Claude (Anthropic) in order to assist with copy-editing and proofreading the manuscript text. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econedurev.2026.102789.

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