The College Melting Pot: Peers, Culture and Women's Job Search*

Federica Meluzzi†

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Abstract

Gender norms are widely recognized as key drivers of persistent gender gaps in the labor market, yet little is known about how these norms evolve or can be influenced. This paper provides new evidence that exposure to university classmates born in more gender-equal environments shapes women's early-career labor market outcomes. I exploit quasi-random, cross-cohort variation in the geographical origins of peers within Master's programs in Italy, leveraging comprehensive administrative and survey data covering the universe of students. Exposure to female classmates born in provinces with one standard deviation higher female labor force participation significantly increases women's likelihood of entering full-time jobs and sorting into higher-paying occupations, reducing early-career gender gaps by 20–40%. Using new data I collected on students' job-search preferences and beliefs, I show that peer effects operate primarily through two channels: reductions in the value women place on hours' flexibility, and learning about job offer arrival rates. Peer effects are highly asymmetric, concentrated among women from less gender-equal regions, indicating that exposure can mitigate early-career disadvantages rooted in childhood environments. The results underscore the potential of educational policies that promote geographical diversity to shift gender norms and advance gender equality in the labor market.

JEL classification: J16, J22, I24, R23, Z13. **Keywords**: gender gaps, female labor supply, childhood environment, peer effects.

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†Bocconi University. E-mail: federica.meluzzi@unibocconi.it

1 Introduction

Cultural norms are pervasive and shape the payoffs to many individual decisions. One critical domain where their influence is particularly pronounced is in the economic behavior of men and women. By shaping beliefs and preferences, gender norms are widely recognized as key determinants of the persistent gender gaps in the labor market—above and beyond traditional factors such as human capital, comparative advantage, or discrimination (Bertrand (2020), Cortes and Pan (2023)). Even as the economic costs of conforming to traditional gender roles have risen, their persistence continues to hinder gender convergence in the labor market (Fernandez (2013), Fortin (2015), Kleven (2024)).

Understanding the determinants of cultural change is therefore a significant yet insufficiently understood problem. While some studies examine cultural change as an intergenerational learning process (Fogli and Veldkamp (2011), Fernandez (2013)), most of the literature documents the persistence of norms rather than uncovering the drivers of change (Giuliano (2020)). In particular, we have limited evidence on whether, and how, the social environment or public policy can influence gender norms, reflecting the scarcity of empirical settings and data that allow for credible identification.

This paper provides new evidence that exposure to college classmates from more gender-equal areas significantly shapes women's labor market behavior. Exploiting quasi-random, cross-cohort variation in the geographic origins of students within Master's programs, together with comprehensive administrative and survey data covering the near-universe of Italian students, I show that peer exposure significantly reduces the large gender gap in full-time employment that emerges at graduation. A key innovation of the paper is to ask *why* being exposed to peers born in more egalitarian places affects women's (and not men's) labor market decisions. Drawing on detailed data on students' job-search preferences and beliefs, I find that these peer effects are driven by (i) changes in women's job-search preferences and (ii) social learning, rather than improved academic outcomes or beneficial labor market connections.

Italy offers a compelling setting to study cultural norms. First, it exhibits exceptionally wide geographic variation in gender equality, with female-to-male labor force participation rates ranging from 44% to 86% across provinces, mirroring the scale of cross-country differences.[1] Due to substantial internal mobility (affecting about 60% of students), Italian universities bring together students from provinces with varying levels of gender equality, who systematically differ in their beliefs about gender roles and their labor market expectations. Moreover, the small size of Master's programs (with a median of 35 students)

[1] These disparities in labor force participation align closely with strong differences in gender attitudes, firms' gender preferences in hiring, and differential full-time employment rates between female and male university graduates.

and the two-year duration of graduate studies create an environment of close social interactions and repeated exchanges of information about labor market opportunities and aspirations.

Women raised in more or less gender-equal provinces systematically differ in their beliefs regarding gender roles and their expectations about labor market opportunities, which translate into divergent early-career outcomes. This relationship is estimated using a refined *epidemiological approach*, focusing on graduates who work in a different province from where they were born (about half of the sample).[2] The core idea is that, conditional on studying in the same Master's program and working in the same local labor market, individuals share similar human capital and job opportunities but differ in their early-life exposure to female role models and gender norms. The results show that women (but not men) from provinces with higher female labor force participation are more likely to enter full-time employment post-graduation. These patterns are robust to controls for academic performance and other observables, and cannot be explained by differential selection into migration.

This paper asks: *Does being surrounded by peers from more (or less) gender-equal backgrounds in college shape women's labor market behavior?* Identifying such peer effects is challenging, since students self-select into programs, so that peer groups are not randomly assigned. To overcome selection issues, I exploit a key feature of the setting: because Master's programs are small, they exhibit substantial cohort-by-cohort variation in the geographic origins of enrolled students, which generates quasi-random exposure to peers from different cultural backgrounds. I leverage this variation to estimate the causal effect of peer exposure to gender norms—measured primarily by female labor force participation (FLFP) in students' home provinces, along with alternative gender-related indicators.[3] This analysis is made possible by access to rich longitudinal data that track changes in peer composition over time across 1,572 Master's programs, a key advantage over existing datasets on university graduates, which are typically limited to smaller samples from selective institutions. For this design to yield causal estimates, changes in peer composition must be orthogonal to time-varying unobserved determinants of students' labor market outcomes. Leveraging high-quality information on a broad set of predetermined individual characteristics—including students' educational histories, academic performance, and family background— I probe the validity of this approach through an extensive set of standard and novel randomization checks.[4]

[2]This approach is similar to recent studies by Kleven (2024), Charles et al. (2024) and Boelmann et al. (2025).

[3]This strategy builds on the research design introduced by Hoxby (2000), and widely used to estimate the impact of students' characteristics on educational outcomes.

[4]These include balancing tests, placebo estimates, and simulation-based evidence showing that the identifying variation resembles random shocks. I also exclude programs with potential non-random

I document three main findings. First, exposure to female classmates from provinces with higher female labor force participation significantly increases women's likelihood of entering full-time employment after graduation. This effect operates in part through greater sorting into occupations where full-time work is more prevalent. The magnitude is economically meaningful: a one standard deviation increase in peers' provincial FLFP (8.5 percentage points) raises women's probability of full-time employment by 2 percentage points, increases weekly hours worked by 3.3%, and translates into a 3.7% gain in net monthly earnings. In contrast, men's outcomes remain unaffected, implying that peer exposure narrows early-career gender gaps by 21 to 40%, depending on the outcome. Importantly, these effects are not driven by broader provincial characteristics: they remain robust across a range of gender-specific indicators and fade or disappear when using non-gender-related measures, such as per capita income or proxies for overall economic activity.

Second, peer effects exhibit a strong asymmetry across the FLFP distribution: the beneficial impacts of peer exposure are concentrated entirely among women from low-FLFP provinces, while women from more gender-equal backgrounds do not respond to peer composition. Such non-linearities suggest that targeted reassignments of students across peer groups could raise average female earnings overall. Moreover, the setting allows for a direct comparison between horizontal (peer-based) and vertical (origin-based) influences. A one standard deviation increase in the proportion of female classmates from high-FLFP provinces—equivalent to nine additional peers—closes up to 65% of the labor supply gap between women from low- and high-FLFP origins, indicating that peer exposure substantially mitigates early-career disadvantages rooted in childhood environments.

Third, I explore the mechanisms behind these peer effects, a question that remains underexplored due to limited datasets tracking beliefs, preferences, and other difficult-to-observe factors (Sacerdote (2011)). Understanding these channels is essential for designing policy interventions that can replicate the benefits of peer exposure without changing group composition (Barrios Fernandez (2023)). Using novel data, I test several potential mechanisms and find evidence for two main channels. First, I find no indication that exposure to high-FLFP peers improves women's academic performance, increases migration to stronger labor markets, or leads to referrals to better jobs. This suggests that peer effects are not driven by better credentials or expanded opportunities, but by changes in preferences and beliefs. Drawing on data from a mandatory institutional survey at graduation, I analyze students' valuations of job attributes. Women exposed to peers from high-FLFP provinces place less value on non-pecuniary attributes—particularly flexibility, leisure time, and the social value of work. These findings contribute to a growing

changes in students' composition and flexibly control for program- and region-specific time trends.

literature on gendered job-search preferences,[5] showing that such preferences are shaped by the social environment and remain malleable into early adulthood.

Finally, I field a targeted survey to examine how beliefs and information diffusion drive peer effects. I administered the survey in person to two cohorts of Master's students across several programs at a large university, achieving a 97% response rate among attending students. The first key finding is that women from low-FLFP provinces enter university with more pessimistic beliefs about full-time employment and view ambition as less socially acceptable. Holding job-search effort and job type constant, they anticipate receiving 13% fewer full-time job offers than women from high-FLFP areas seeking jobs in the same region.[6] These expectations are strong predictors of job outcomes and account for about one-fifth of the observed full-time employment gap between students from low- and high-FLFP origins. These results underscore the role of information frictions, alongside preferences and attitudes, in perpetuating norms around female labor market participation. I also document convergence in labor market beliefs during the course of graduate study. Between the first and second year, the initial gap in expectations about full-time job offers narrows by over 70%, driven entirely by upward revisions among women from more traditional backgrounds. This asymmetric belief updating closely mirrors the non-linear peer effects discussed earlier and offers compelling evidence that social learning plays a role in shaping labor market expectations. In contrast, gaps in perceived gender roles remain largely stable over time, echoing past evidence that such views are more resistant to change (Giavazzi et al. (2019)).

Related literature. This article contributes to three strands of research. First, a large body of work, following the seminal contribution of Fernandez (2007), has documented the persistent role of cultural norms in shaping women's economic decisions, particularly around the time of motherhood (e.g., Antecol (2000), Fernandez and Fogli (2009), Blau et al. (2011), Fortin (2015), Bertrand et al. (2015), Cortés et al. (2022), Ichino et al. (2024), Kleven (2024), Boelmann et al. (2025)). I complement this work by showing that early exposure to gender norms influences women's labor supply choices already at labor market entry—well before family formation—potentially compounding later-life effects. More importantly, while the mechanisms behind cultural persistence remain poorly understood, I identify a novel channel: survey evidence reveals that women from more traditional backgrounds systematically underestimate their chances of receiving full-time offers. These

[5]See Mas and Pallais (2017), Wiswall and Zafar (2018), Wiswall and Zafar (2021), Le Barbanchon et al. (2021), Fluchtmann et al. (2024), Caldwell and Danieli (2024).

[6]These beliefs also correlate with perceived employer discrimination. By contrast, I find no regional differences in fertility expectations or intended labor supply post-motherhood, possibly consistent with recent evidence that individuals often misperceive motherhood-related career costs (Kuziemko et al. (2018)).

expectations shape job search behavior and early-career outcomes, reinforcing inequality through an anticipatory mechanism. This channel has direct policy relevance: relatively low-cost interventions, such as improving access to accurate labor market information, could meaningfully reduce gender gaps, especially among women from traditional backgrounds. These results complement recent work by Bursztyn et al. (2020) and Cortés et al. (2022), who emphasize information frictions, such as misperceptions about second-order beliefs, in the persistence of gender norms.

Second, this paper contributes to the small but growing literature on the transmission of gender norms—an area where empirical evidence remains limited (Giuliano (2020)). Most existing work emphasizes intergenerational channels, particularly maternal influence: for example, Olivetti et al. (2020), Mertz et al. (2024), and Kleven et al. (2024b) show that women's labor market and occupational choices are shaped by the employment behavior of their classmates' mothers during childhood and adolescence. More closely related, an emerging set of studies examines horizontal transmission through peers, such as coworkers (Boelmann et al. (2025)) and neighbors (Maurin and Moschion (2009), Jessen et al. (2024)). My contribution is twofold. First, I provide the first large-scale evidence on how exposure to culturally diverse college classmates affects gendered labor market outcomes. Leveraging variation in peer composition across cohorts within Master's programs, I show that women from more traditional backgrounds significantly increase full-time employment rates when exposed to peers from more gender-egalitarian regions—partially offsetting the disadvantages of their childhood environments. Second, I go beyond documenting peer effects and provide direct evidence that they operate through shifts in preferences and beliefs, rather than improved opportunities, complementing previous work that emphasizes the role of peers in providing labor market connections (Kramarz and Skans (2014), Zimmerman (2019), Fischer et al. (2023), Hampole et al. (2024), Campa (2025), Einiö (2025)).

Third, this study contributes to the growing literature on job seekers' misperceptions about the labor market. While standard search models assume rational expectations, a large body of evidence documents systematic belief distortions (see Mueller and Spinnewijn (2023) for a review). Across diverse settings, individuals tend to overestimate their job-finding probabilities (Spinnewijn (2015), Caliendo et al. (2015), Conlon et al. (2018), Arni (2019), Potter (2021), Mueller et al. (2021), Bandiera et al. (2023), Banerjee and Sequeira (2023)), and misperceptions have also been identified regarding expected wages and outside options (Drahs et al. (2018), Cortes et al. (2023), Alfonsi et al. (2024), Jäger et al. (2024)). This paper contributes along three dimensions. First, I study beliefs about the arrival rates of part-time versus full-time job offers—a dimension previously overlooked. My elicitation method holds job-search effort constant, isolating beliefs about

labor demand. Second, I document substantial heterogeneity by early-life environment: women from low-FLFP regions hold more pessimistic expectations, which persist despite migration and explain part of their higher likelihood of working part-time. Third, I provide new evidence on belief updating: over the course of the Master's program, women from more traditional provinces substantially revise their expectations. This convergence is consistent with social learning and highlights the role of peer exposure in reducing information frictions.

The paper proceeds as follows. Section 2 introduces the institutional setting and data. Section 3 describes the "melting pot" at Italian universities. Section 4 documents early-career gender earnings gaps and estimates cultural persistence. Section 5 outlines the identification strategy and assesses its validity. Section 6 presents the main peer-effect estimates, and Section 7 tests their robustness across specifications and samples. Section 8 examines non-linearities, and Section 9 investigates underlying mechanisms. Section 10 uses new survey data on beliefs to deepen the analysis of cultural persistence and social learning. Section 11 concludes with implications for education policy.

2 Institutional Background and Data

2.1 Admission and Functioning of Graduate Education

Admission to Master's Programs. Since the early 2000s, higher education in Italy has followed a two-cycle structure consisting of a three-year bachelor's degree (*laurea triennale*) followed by a two-year master's degree (*laurea magistrale*). This structure was introduced as part of the Bologna Process, launched in 1999 to harmonize higher education systems across the European Higher Education Area (EHEA). Although formally distinct, progression between the two cycles is common: approximately 70% of students enroll in a master's program upon completing their bachelor's degree.

Admission to master's programs is conditional on satisfying curricular prerequisites, primarily a minimum number of credits in specified subject areas. Students may therefore change fields between undergraduate and graduate studies, provided they meet these eligibility requirements.[7] In addition to curricular criteria, many programs are selective. Admissions decisions commonly rely on entry examinations, undergraduate grade point averages, and, in some cases, interviews. Applicants are typically ranked based on these criteria, and admission is competitive. Additional application requirements—such as English language certifications, motivation letters, or reference letters—may vary across institutions and programs. Only a limited number of fields, including medicine, health sciences, architecture, psychology, and primary education, are subject to a centralized

[7]For example, admission to a master's program in economics typically requires at least 53 credits in economics, statistics, or related social sciences.

national entrance examination.

Throughout the paper, a *degree* refers to a master's program at a given university; a university *course* denotes an individual subject within a degree program, associated with a specified number of academic credits; and a *field of study* refers to a broad disciplinary category (e.g., economics) that may be offered by multiple institutions.

Tuition Fees. Approximately 90% of Italian students are enrolled in public universities. Tuition fees vary across institutions and degree programs and are generally income-contingent. Regional governments set income thresholds for eligibility for need-based grants, which may cover tuition fees, housing, and meal vouchers. In the sample used in this paper, 23% of students receive such financial aid. Among students who are not grant recipients, the average annual tuition fee is €1,262.

2.2 Data Sources and Sample

The empirical analysis draws on multiple data sources. The core of the analysis relies on comprehensive administrative records from university registries, covering approximately 93% of students enrolled in Italian universities. These records include nearly all public institutions and a selected group of private universities affiliated with the AlmaLaurea consortium.[8] The administrative data are linked to institutional pre-graduation surveys and to post-graduation follow-up surveys conducted by AlmaLaurea, which allow me to track students' labor market outcomes after graduation and to observe detailed information on their job-search behavior and preferences. In addition, I designed and administered an original survey to collect students' beliefs at different points during the master's program.

Administrative student-level data. The administrative records contain detailed information on students' academic performance during the master's program, including the number of exams taken, GPA, and final degree grade. They also include data on high-school education (school type and grades), demographic characteristics (age, immigration status, and municipality of birth and residence), unique identifiers for master's programs within universities, and precise enrollment and graduation dates. I use these data to identify peers within programs and to construct measures of students' geographical background, based on their province of residence (or birth) prior to enrollment. The administrative nature of the data ensures full population coverage, allowing me to observe the complete set of peers within each program.

[8] A full list of participating universities is available at: https://www.almalaurea.it/chi-siamo/gli-atenei.

Institutional pre-graduation survey. As part of the graduation process, students are required to complete a pre-graduation survey administered by their university. The survey is compulsory and is administered after students have passed all required exams, resulting in a response rate close to 100%.[9] The survey collects detailed information on students' job search intentions and preferences, including their valuation of different job attributes. It also gathers information on students' socio-economic backgrounds, such as parents' occupations and education levels. In addition, the survey provides detailed information on students' educational histories, including high school and bachelor's degree characteristics, prior academic performance, and work activities undertaken during their studies.

Follow-up surveys. The AlmaLaurea consortium conducts standardized follow-up surveys one, three, and five years after graduation. Because the cohorts in my sample are recent, the analysis primarily relies on the one-year follow-up survey. Students are initially contacted by email and subsequently by phone if necessary, resulting in high response rates. One year after graduation, response rates are 73.7% for women and 73.2% for men.[10] The survey collects detailed labor market information, including net monthly earnings, usual weekly hours (including overtime), contract type (e.g., part-time versus full-time), job security, occupation, industry, and job location. Earnings and hours worked are reported in bins, which I convert into continuous measures using bin midpoints.[11] The survey also includes retrospective questions on job-search activities and current search behavior.

Survey on students' beliefs. Empirical analysis of the mechanisms underlying peer influence is often constrained by data limitations. To address this gap, I designed and administered an original survey to elicit students' beliefs about gender attitudes and a range of outcomes, including social expectations, perceived employer discrimination, expectations about their own labor market prospects, parameters of a job-search model, and anticipated fertility and labor supply decisions. The survey also collects information on network structure and perceived peer influence. It was administered in fall 2023 to two cohorts of students enrolled in a sample of master's programs at a large university. Using in-person administration and lottery incentives, I achieved a 97% response rate among attending students. Further details on the survey design and elicitation procedures are

[9] Although students may formally decline to complete the survey or withhold consent for data use, over 90% of graduates both complete the questionnaire and authorize the use of their data for research.

[10] Response rates decline to 70.4% and 70.3% after three years, and to 64.2% and 64.3% after five years.

[11] For example, reported earnings are categorized as $<$ €250, €250–€500, €500–€750, €750–€1000, ..., $>$ €3000. I assign €187.50 to the lowest category and €3750 to the top-coded category. Weekly hours are categorized in five-hour intervals from "$<$ 5 hours" to "$>$ 60 hours."

provided in Section 10.

2.3 Sample description

This paper focuses on students enrolled in master's programs between 2012 and 2016.[12] I restrict the sample to degree programs that (i) enroll at least one male and one female student within the same cohort, and (ii) satisfy this condition for at least two consecutive years. These restrictions exclude 3.55% and 6% of students, respectively. The final sample consists of 316,470 students enrolled in 1,572 degree programs across 71 universities, including 182,792 women and 133,678 men. The sample includes only students who remain enrolled for the full duration of their master's program.[13]

Background characteristics and academic records. Table 1 reports descriptive statistics on background characteristics and academic performance, disaggregated by gender. The final column presents p-values from tests of equality of means between female and male students. The statistics combine information from administrative records and the institutional survey, the latter being available for 91% of students.

Women outperform men academically across several dimensions. They achieve higher GPA and final graduation grades during their master's studies and exhibit stronger prior academic performance, including higher high school and bachelor's degree grades. Women are also more likely to have attended an academic-track high school (*liceo*), with 84.2% doing so compared to 71.4% of men. The dispersion of academic outcomes is smaller among women. In terms of field specialization, women are less likely to choose scientific tracks and are more concentrated in the humanities, both in high school and at university. The largest disparities arise in engineering and humanities: 27% of men study engineering, compared to 8.2% of women, while 24.7% of women and 10.4% of men pursue humanities. By contrast, similar shares of female and male students enroll in science, chemistry, or biology programs at university (approximately 13%).

Regarding family background, approximately 20% of female students have parents with tertiary education, and about one-third have fathers employed in high–socioeconomic status (SES) occupations. Male students are more likely to come from relatively advantaged backgrounds, as reflected in higher parental education and a greater share of fathers in high-SES occupations. While nearly all fathers are in the labor force, maternal labor force participation stands at 71% for women and 73% for men in the sample, exceeding national averages.

[12] Since the available data are organized by graduating cohorts, I reconstruct enrollment cohorts using students' enrollment and graduation dates recorded in university registries.

[13] A limitation of this approach is the exclusion of dropouts, who represent approximately 6% of enrolled students during the 2012–2016 period (ANVUR, 2023).

Labor market outcomes and the job-search process. Table 2 presents summary statistics on labor market outcomes based on responses to the follow-up survey conducted one year after graduation. Response rates are high and balanced across genders, at 73.7% for women and 73.2% for men. At the time of the survey, approximately 12% of both female and male graduates are pursuing further education, either at the master's or PhD level, while the majority have entered the labor force. Among respondents, 66.6% of women and 71.3% of men are employed, either under a standard employment relationship or through an internship. Unemployment is slightly higher among women, with 16% actively searching for a job compared to 12.1% of men, while 5.2% of women and 4.0% of men are not actively seeking employment. As discussed below, these differences in labor force participation largely reflect variation in fields of study.

Among employed graduates, women experience less favorable labor market outcomes than men. Average monthly earnings amount to €1,077.8 for women, compared to €1,324 for men. Although the vast majority of women (93.6%) express a preference for full-time employment, as measured in the institutional survey,[14] 30.7% of women are employed part-time, compared to 13.8% of men. Women are also underrepresented in occupations and industries characterized by above-median earnings and higher rates of full-time employment. They are more likely to work in the public sector and less likely to hold permanent contracts. Women are also twice as likely as men to be employed in the informal sector.

Turning to job-search behavior, over 80% of both women and men are in their first post-graduation job. Women report having held slightly more jobs, consistent with shorter contract durations or more frequent job transitions. Most graduates begin searching for a job within one month of graduation. On average, women accept their first job offer within three months, compared to 2.7 months for men.[15] Women also report lower satisfaction with their job outcomes, as reflected in higher rates of on-the-job search. Dissatisfaction is particularly pronounced among part-time employed women: 58% are actively seeking another job, compared to 30.8% of women in full-time positions. Women are also more likely to experience skill mismatch, as indicated by lower rates of using skills acquired during their master's degree.

[14]Preference for full-time work is based on responses to the questions "Are you available to accept a full-time position?" and "Are you available to accept a part-time position?" Responses range from "Not at all" to "Absolutely yes." Students more inclined to accept a full-time than a part-time position are classified as preferring full-time work.

[15]This variable measures the number of months after graduation at which job search begins, with "0" indicating individuals who start searching before or immediately after graduating.

3 The College Melting Pot

This section highlights three distinctive features of the Italian setting that make it well suited for studying the effects of exposure to peers born in diverse areas. First, Italian universities function as a "melting pot", attracting students from regions with markedly different levels of gender equality in labor market participation. Second, students are enrolled in relatively small Master's programs, which foster close and sustained peer interactions. Together, these features create an environment in which students from diverse backgrounds interact intensively, providing a natural setting to examine how peer exposure shapes beliefs and behaviors.

3.1 Heterogeneity in Female Labor Force Participation Across Birth Provinces

A defining feature of the Italian context is the pronounced variation across provinces in female labor market participation.[16] For instance, the ratio of female to male labor force participation (FLFP/MLFP) ranges between 43% and 86%. These disparities are closely associated with regional differences in attitudes toward gender roles. Disagreement with statements such as "*Being a housewife is just as fulfilling as working for pay*" or "*Men should be given priority when jobs are scarce*" varies widely across Italian regions, from 16% to 67%, according to recent waves of the European Values Survey (EVS, 2008). The magnitude of this regional heterogeneity is comparable to that observed across countries.

Such variation implies that students are born and raised in markedly different gender-related environments. I exploit this feature by constructing proxies for local gender equality based on a set of geographic indicators:

1. Female labor force participation (FLFP hereafter) for different age groups, measured at the province level;
2. The ratio of female to male labor force participation (FLFP/MLFP hereafter) for different age groups, measured at the province level;
3. The percentage of private-sector firms without hiring preferences for male workers, measured at the province level;
4. The percentage of female college graduates employed full-time at the beginning of their careers, measured at the regional level;
5. The ratio of female to male college graduates employed full-time at the beginning of their careers, measured at the regional level;

[16] See: Campa et al. (2011), Carlana (2019), Casarico and Lattanzio (2023), Carrer and de Masi (2024).

6. Historical literacy rates of women relative to men, measured at the province level.

Most indicators are measured at the province level (NUTS-3 classification). Italy is divided into 103 provinces, which are administrative units between municipalities and regions.[17] Students are assigned to provinces based on their place of residence at university enrollment, as recorded in university registers. This measure can be interpreted as the location where the student was born and raised: for approximately 80% of the sample, province of residence and province of birth coincide.

Because these measures aim to capture the gender-related environment to which students were exposed during their formative years, they are constructed using data from periods prior to university enrollment, primarily reflecting adolescence. The first two indicators—province-level averages of FLFP and the FLFP/MLFP ratio—are computed using data from 2004 to 2007. Measures of firms' gender preferences in item (3) are based on responses to a nationally representative survey of approximately 100,000 Italian firms conducted in 2003 (*Indagine Excelsior*, Unioncamere), which covers about one-third of firms in manufacturing and services.[18] I further incorporate labor market outcomes of earlier cohorts of female graduates, who likely constitute salient reference groups for current students. To construct these measures, I use data from preceding cohorts and focus on the labor market behavior of *stayers*—students who work in their region of origin—to compute the share of female graduates employed full-time one year after graduation, both in absolute terms and relative to male graduates. Owing to data limitations in smaller provinces, these indicators are aggregated at the regional level (NUTS-2). Finally, I include a historical proxy based on the ratio of female to male literacy rates from the 1911 Italian Census.

Summary statistics of gender equality indicators. Table 1 reports summary statistics for the gender-related indicators described above and documents substantial cross-province variation across all measures. FLFP ranges from as low as 27%—a level comparable to that observed in low-income countries—to values exceeding the OECD average. Among younger women (ages 25–34), FLFP varies between 38% and 86%. Crucially, this variation does not simply reflect overall labor market conditions. The FLFP-to-MLFP ratio, which isolates gender-specific differences, ranges from 43% to 86% for the general population and from 47% to 95% among young adults.[19] In contrast, male labor force

[17] As of 2010, the average population of a province was 551,000, though there is substantial variation. The largest province, Rome, has over 4 million residents and includes 121 municipalities, while the smallest, Ogliastra in Sardinia, has fewer than 60,000 residents and only 23 municipalities.

[18] Since 1997, the Excelsior Survey—run in partnership with the Ministry of Labor, ANPAL, and the EU—has collected annual information on firms' hiring intentions, including preferences for male, female, or no gender preference.

[19] A visual illustration of these measures is provided in Figure 1.

Table 1: Summary Statistics of Geographical Indicators of Gender Equality

	Mean	SD	Min	Max	Obs
Female labor force participation (age: 15–64)	49.7	11.2	27.3	66.7	316,470
Female/Male labor force participation (age: 15–64)	66.7	11.8	43.0	85.7	316,470
Female labor force participation (age: 25–34)	65.1	15.2	38.0	86.0	316,470
Female/Male labor force participation (age: 25–34)	74.3	13.0	47.0	95.0	316,470
Male labor force participation (age: 15–64)	73.8	4.5	62.9	81.9	316,470
Male labor force participation (age: 25–34)	86.7	6.5	71.4	97.1	316,470
% of female graduates in full-time job	56.4	9.5	40.1	68.9	316,470
% of female/male graduates in full-time job	71.8	6.7	55.3	83.5	316,470
% of firms without hiring pref. for male workers	54.3	8.9	35.0	71.0	316,470
Historical literacy rates of female/male	81.7	13.1	54.0	100.0	316,470

Notes. The table presents summary statistics of indicators capturing the local gender-related environments to which students were exposed early in life (items 1–5 in Section 3). The unit of observation is the individual student, who is assigned to a province based on their place of residence prior to enrollment in the Master's program.

participation (MLFP) exhibits much narrower geographic variation, with a range less than half as wide as that of FLFP. Substantial differences are also evident in other labor market indicators. For example, the female-to-male ratio of college graduates employed full-time varies between 55% and 83%, and the share of firms reporting no preference for male hires ranges from 35% to 71%. Table 3 presents these measures separately by gender and shows no systematic differences in the geographical origins of female and male graduates.

Beyond gender-specific measures, provinces also differ along other social and economic dimensions, summarized in Table 4. Several of these characteristics are moderately to strongly correlated with FLFP across provinces, including male labor force participation (MLFP), per-capita income, and the availability of childcare services (Table 5). In light of these correlations, a dedicated analysis examines whether the estimated peer effects reflect broader exposure to local role models and labor market conditions, rather than gender-related factors alone.

3.2 Mobility Outside Birth Provinces

A second key feature of the Italian context is the high rate of student mobility across provinces. Due to historical and institutional factors, the majority of Italian students relocate to attend university (ANVUR, 2023). This pattern has deep roots and has remained relatively stable over time. During the period covered by this analysis, more than 57% of students enrolled in a university located outside their province of residence, and 31% moved to a different region to pursue higher education.

The institutional landscape helps explain this widespread student migration. As of 2016, Italy had 89 public universities—which serve over 90% of the student popula-

tion—but these institutions were located in only 52 of the country's 103 provinces. Moreover, not all fields of study are available at every university, as many institutions are specialized.[20] Roughly 20% of Italians aged 18–19 reside in provinces without any higher education institutions, and only 77% have access to both STEM and non-STEM programs within their home province (Braccioli et al., 2023). In addition, students face no restrictions on applying to universities outside their region or province of residence. Together, these institutional features—combined with regional disparities in post-graduation labor market opportunities—contribute to the high level of inter-provincial student mobility observed in the data.

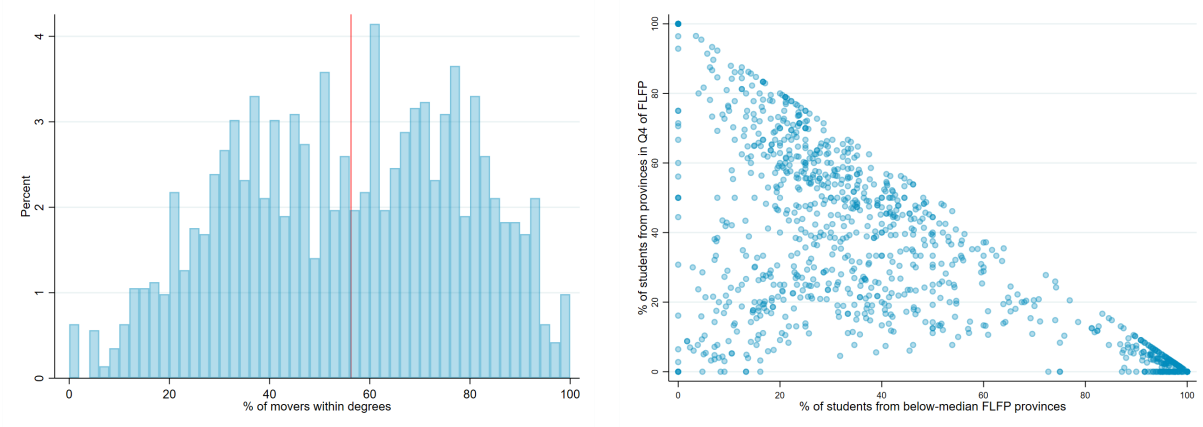
Mobility patterns in the sample. Table 6 reports student mobility by gender. 58.9% of women and 55.4% of men move outside their birth province to pursue university studies. Mobility destinations do not differ markedly by gender: students of both sexes tend to relocate to areas characterized by more egalitarian gender environments relative to their provinces of origin. Importantly, movers are present across all degree programs: fewer than 1% of programs have no movers, while in 50% of programs, more than 56% of students are movers (Figure 1, Panel A). Mobility remains high at the job-search stage. Table 7 reports summary statistics on mobility into local labor markets for students employed one year after graduation. A substantial share of graduates work outside their province of origin: 51.6% of men and 44.1% of women. The majority of students—68.4% of women and 65.3% of men—obtain their first job in the same region where they attended university. In addition, around 5% of both female and male graduates move abroad for work.

Table 8 examines women's mobility patterns by quartile of FLFP in their province of origin. Substantial out-migration is observed across all quartiles, with women from low-FLFP provinces migrating over longer distances and more often leaving their home region entirely. Among women who migrate, destination patterns differ markedly. Those from high-FLFP provinces tend to relocate to areas with similarly high FLFP, resulting in unequal exposure to peers' backgrounds. Specifically, women from high-FLFP provinces enroll in programs in which 67% of peers originate from above-median FLFP areas, compared to 27% for women from low-FLFP provinces. Differences in field of study are modest across groups. Women from low-FLFP provinces are slightly more likely to pursue degrees in scientific disciplines, engineering, and psychology, whereas women from high-FLFP areas more often choose fields such as humanities, economics, statistics, and architecture. Patterns of return migration also differ: 54.8% of women from low-FLFP provinces work outside their province of origin after graduation, compared to 37.8% of women from high-FLFP areas, as shown in the bottom panel.

[20]For instance, degrees in information technology were offered at only 29 universities, and agriculture and veterinary sciences at just 24 institutions.

Peers' diversity within Master's programs. Due to high student mobility, Master's programs exhibit substantial heterogeneity in the geographical origins of their enrolled students. Panel (B) of Figure 1 illustrates this "melting pot" by mapping each program according to the share of students originating from high-FLFP provinces (y-axis) and from below-median FLFP areas (x-axis). More than one-third of programs are composed exclusively of students from below-median FLFP regions. At the same time, the majority of programs display a more balanced mix across quartiles, clustering near the center of the distribution and thus including students from all FLFP quartiles. A smaller fraction—approximately 5% of programs—consists entirely of students from above-median FLFP areas. A more detailed view of the distribution of students' geographical origins across degree programs is provided in Figure 2.

Figure 1: Geographical Composition and Mobility of Students Within Degree Programs



(a) Mobility **(b)** Geographical origins

Notes. Panel (A) plots degree programs by the share of students who are movers in 2016. Each unit corresponds to a degree program (N = 1,572), and the red line indicates the median across degrees. Panel (B) plots degree programs (N = 1,572) by the share of students originating from provinces in the highest quartile of FLFP (y-axis) and the share originating from provinces in the first or second quartiles of FLFP (x-axis). Data refer to 2016.

3.3 Size and Relevance of Peer Groups

The relatively small size of Master's degree programs in Italy provides a particularly suitable context for studying peer effects. Unlike much of the existing literature, which often defines peer groups broadly—for example, encompassing all students within the same school or university cohort—this study focuses on a more granular and potentially more meaningful peer group: students enrolled in the same Master's program and cohort. These programs are typically small, with a median (mean) size of 35 (48) students and a range from 4 to 410 (Figure 3, Panel (A)). Gender composition is generally balanced

across programs, with few exhibiting strong male or female dominance (Panel (B)).[21]

This structure offers two main advantages. First, the small size of peer groups facilitates interactions among students and limits the scope for endogenous sorting into subgroups—a common concern in larger academic environments (Carrell et al., 2013). Peer interactions are further reinforced by the duration of exposure: students typically spend at least two years within the same cohort. Institutional design also strengthens this shared exposure. As mandated by Ministerial Decree 270/2004,[22] a substantial share of course content is standardized within each degree program, while students have autonomy over only about 10% of their total credits. This curricular structure ensures that students attend a common set of classes with the same peers throughout their studies.

Second, the small size of programs is central for identification. I exploit the fact that small programs experience meaningful fluctuations in cohort composition over time. Such variation is much less likely in large programs, where the law of large numbers implies that cohort composition converges toward its average, limiting scope for cohort-to-cohort variation.

Quantity and quality of social interactions. Evidence from the original survey conducted at the University of Bologna (Section 10) documents the intensity and relevance of peer interactions. Table 4 summarizes key findings on students' social networks, revealing strong ties: more than 70% of students spend leisure time with classmates at least weekly. Geographic homophily is limited—only 10% of students primarily socialize with peers from their province of origin, while 32% mainly interact with peers from other provinces and 58% report balanced interactions. Career-related discussions are frequent, particularly among same-sex peers. Among female students, 80% discuss career aspirations with female classmates (63% with male peers), with 46% and 20% reporting that these conversations occur often or very often, respectively.

4 Two Facts About Early-Career Gender Gaps

4.1 The early-career Gender Earnings Gap

Despite achieving higher levels of human capital—as reflected in their higher GPA and stronger prior academic records—women earn 11% less per month than observationally similar male peers from the same Master's program (Table 2).[23] This gap is both statistically significant and economically meaningful, corresponding to an average annual net

[21] Additional program-level characteristics are summarized in Table 9.

[22] Ministerial Decree 270/2004 regulates the structure of university degree programs in Italy, including the proportion of fixed and elective course content.

[23] This finding is consistent with Bovini et al. (2023), who use individual-level administrative data linking university education and social security records for all graduates in Italy between 2011 and 2018.

difference of approximately €1,795.

Table 2: The Gender Earnings Gap At Labor Market Entry

	(1) Log(monthly earnings)	(2) Log(weekly hours)	(3) Pr(fulltime)	(4) Log(wage)
Female	-0.113***	-0.083***	-0.051***	-0.029***
	(0.004)	(0.003)	(0.003)	(0.003)
GPA	✓	✓	✓	✓
Degree FEs	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓
Observations	127,153	127,153	127,153	127,153
R-squared	0.294	0.259	0.293	0.089

Notes. The table reports coefficients from regressions of graduates' labor market outcomes on a female indicator, controlling for GPA and including degree and cohort fixed effects. Column (1) shows results for log net monthly earnings. Column (2) presents log weekly hours worked. Column (3) uses a binary indicator for holding a full-time contract (typically 40 hours/week). Column (4) reports log hourly wages. The sample includes graduates employed under standard contracts (excluding internships or training programs) one year after graduation. Standard errors are clustered at the degree level.

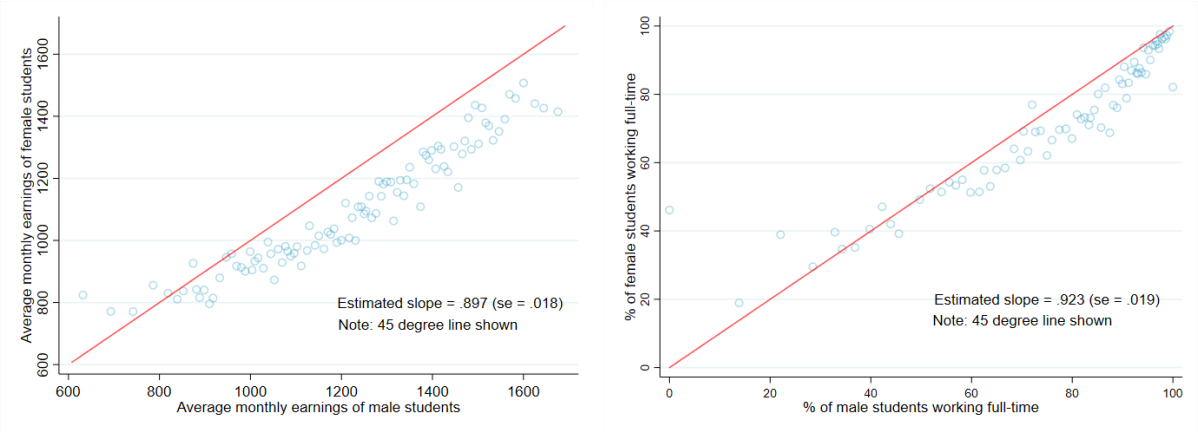
The earnings gap is largely explained by differences in hours worked. Women are 5 percentage points less likely to hold full-time positions and report working 8.3% fewer hours per week than male peers with comparable academic profiles.[24] Notably, nearly one-third of the unconditional gender gap in full-time employment (see Table 2) occurs within programs, among students in the same Master's cohort. These earnings differences persist after controlling for occupation and industry fixed effects and are not explained by geographic mobility patterns (Table 11). The residual gender gap in hourly wages is smaller, at 2.9%.

Gender gaps in earnings and employment are pervasive across all programs and fields. Figure 2 plots binned degree-specific effects on monthly earnings and full-time employment for women against those for men. The OLS-estimated slopes—weighted by each degree's student share over all years—reveal a strong positive correlation between male and female average outcomes within degrees. Yet, women consistently earn less (Panel A) and work fewer hours per week (Panel B) than men in the same programs. Crucially, these gaps remain stable and do not narrow over the first five years after labor market entry.

Overall, these descriptive facts provide comprehensive evidence of systematic gender differences in earnings and hours worked at the start of the career among highly skilled individuals in Italy. Prior research—largely based on U.S. samples and often restricted to elite universities or specific fields—typically finds minimal gender gaps in working hours at labor market entry (Cortes et al. (2023)), with disparities emerging only after a few years in the labor market (Bertrand et al. (2010), Azmat and Ferrer (2017)). In

[24]No significant gender differences are found on the extensive margin of employment (Table 10).

Figure 2: Gender-Specific Degree Effects on Earnings and Labor Supply



(a) Net monthly earnings **(b)** Full-time employment

Notes. The figure shows binned scatter plots of estimated degree effects for female students against estimated degree effects for male students. Each degree is characterized by the average earnings (or full-time employment) of male students (x-axis) and the average earnings (or full-time employment) of female students (y-axis), both computed across all years. The slope is estimated across degrees by OLS, after re-weighting each degree for the share of students it represents. In the regression, a unit corresponds to a degree. A 45-degree line is shown in red.

contrast, the Italian context reveals substantial gender gaps from the outset, underscoring important context-specific dynamics in early-career labor market outcomes for highly skilled individuals.

Fertility and couple decisions. A large literature attributes much of the residual gender gap in labor supply to parenthood[25]. However, in this setting, realized fertility does not play a role. The average age of women in the sample is 24, with only 3.7% having children and 16.1% married or cohabiting. Excluding these groups does not affect the gender earnings gap (Table 12). Survey evidence on fertility expectations further indicates that anticipated parenthood is unlikely to explain women's higher likelihood of part-time employment. Women expect their first child around age 31—well after labor market entry—and only a minority foresee reducing hours or exiting the workforce due to motherhood. Section 10 will provide a more detailed exploration of this channel.

Timing of job acceptances. Prior research has suggested that gender differences in job search behavior—such as women accepting earlier offers due to greater risk aversion—may drive early-career earnings gaps (Cortes et al. (2023)). The present data do not support this hypothesis. Men and women initiate their job searches at similar times, but women tend to accept offers later than men (Table 2). Moreover, the gender earnings gap remains

[25]See, e.g., Altonji and Blank (1999), Bertrand et al. (2010), Angelov et al. (2016), Azmat and Ferrer (2017), Kleven et al. (2019), Casarico and Lattanzio (2023), Cortes and Pan (2023), Kleven (2024), Kleven et al. (2024a)

stable throughout the job search period (Figure 5).

4.2 Cultural Persistence

Do early-life exposures to working women shape women's labor supply decisions in early adulthood? I explore this question using an epidemiological approach (Fernandez (2007)) and focus on movers—female graduates who work in a different province than where they were born (roughly half the sample). This strategy isolates the role of early-life social exposure from current labor market and institutional conditions. Specifically, I test whether movers' labor supply varies systematically with the level of gender equality in their birthplace, using the measures introduced in Section 3.1. While the epidemiological method was originally developed to study intergenerational transmission among immigrants, recent work has extended it to internal migration (Kleven (2024), Charles et al. (2024), Boelmann et al. (2025)). The key idea is that movers are exposed to the same labor market conditions at destination, but may bring with them beliefs and preferences shaped by the environment in which they grew up.

I estimate the following equation:

$$Y_{idcp} = \beta_0 + \alpha \times Q4FLFP_{idcp} + \theta_d + \alpha_c + \gamma_p + \left(\sum_{k=1}^{K} \beta_k x_{idcp}^k \right) + \varepsilon_{idcp} \tag{1}$$

where i denotes a female mover who completed a Master's degree d in cohort c and is employed in province p. The variable Q4FLFP equals 1 if she was born in a province in the top quartile of FLFP, and 0 if in the bottom quartile.[26] The model includes fixed effects for degree program, cohort, and province of employment. In some specifications, I also control for GPA and parental occupations. Table 3 shows that women exposed to higher female employment in childhood work significantly more as adults—consistent with a mechanism of *cultural persistence*. Female movers from high-FLFP provinces work 7.6% more hours per week and are 2.2 percentage points more likely to be employed full-time than those from low-FLFP provinces, despite being employed in the same local labor markets and holding the same degrees. These differences translate into a 6.2% earnings premium (roughly €872 annually). The estimates remain stable when controlling for academic performance and family background and are robust across alternative indicators of birthplace gender equality. In contrast, effects weaken substantially when using non-gender-specific characteristics of the province of origin.

[26]For simplicity, I focus only on the two most extreme quartiles, where average FLFP rates are approximately 34% and 62%, although labor supply differences are also observed between the intermediate quartiles, especially between the first and second.

Table 3: Estimates Of Cultural Persistence (Female Movers)

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(weekly hours)			Pr(fulltime)		
Q4 vs. Q1 FLFP	0.072***	0.076***	0.074***	0.025***	0.022***	0.021***
	(0.011)	(0.011)	(0.011)	(0.008)	(0.008)	(0.008)
Province of job FEs		✓	✓		✓	✓
GPA			✓			✓
Parental background			✓			✓
Degree FEs	✓	✓	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓	✓	✓
Observations	15,838	15,835	15,835	15,838	15,835	15,835
Nb. of degrees	1,218	1,218	1,218	1,218	1,218	1,218
R-squared	0.293	0.302	0.304	0.331	0.348	0.350

Notes. The table reports coefficients from separate regressions of women's labor market outcomes on a dummy variable indicating whether the student originates from a province with FLFP in the highest vs. lowest quartile (equation 1). All regressions include controls for degree and cohort fixed effects. Controls for parental background include: FEs for education titles of mother and father (10 classes), FEs for occupations of mother and father (12 classes). The sample consists of female *movers*, defined as women working in a different province from their birth province, who are employed one year post-graduation. Standard errors are clustered at the degree level.

Movers' selection. A key concern in attributing labor supply differences to cultural persistence is the potential for differential selection: women who move out of high- and low-FLFP provinces may differ systematically in observable characteristics. To address this, Table 13 compares the ability, educational background, and socioeconomic profiles of female movers from provinces in the top and bottom quartiles of FLFP, using the same specification as in Equation 1. The results suggest that, overall, movers from high- and low-FLFP provinces are broadly similar. Parental education levels are comparable across groups. Some differences emerge in parental occupations: women from low-FLFP provinces are less likely to have parents in high-SES jobs and more likely to have parents in medium-SES roles, while the share with fathers in low-SES occupations is nearly identical. Mothers' labor force participation—measured by whether the student reports their mother was working at the time of the survey—tracks local labor norms but remains significantly above the national average in both groups. Importantly, this variation in maternal employment does not explain the link between early-life environment and adult labor supply. If anything, women from low-FLFP provinces appear more academically selected: they are more likely to have attended academic-track high schools (*liceo*), particularly in science and humanities, and tend to have higher grades. Overall, these patterns suggest that differences in observable characteristics do not drive the observed relationship between birthplace context and labor supply.

Male outcomes. A second concern is that other local characteristics correlated with FLFP—rather than gender-specific exposure—may shape individuals' beliefs and preferences. If so, similar patterns should emerge among men. To test this, I replicate the epidemiological analysis on male students (Table 14). The results show no significant relationship between men's province-of-origin FLFP and their likelihood of full-time employment. A modest positive association emerges for hours worked, driven by slightly higher rates of overtime, but the magnitude is less than half that observed for women and attenuates once local controls are included.[27]

These results point to a gender-specific mechanism. The persistence in female labor force participation appears to reflect early exposure to working women in one's environment. Potential drivers include the transmission of preferences, gender-role attitudes, information channels, expectations on the availability of jobs in the economy, or other demand-side responses. I explore these mechanisms further in Section 10, drawing on new survey data that reveal large and systematic differences in beliefs linked to FLFP in the province of origin.

5 Identification of Peer Effects

The previous section showed that women exposed to higher female labor force participation in their province of origin tend to work more in adulthood—consistent with a mechanism of cultural persistence. But an important follow-up question arises: how do women respond to exposure to peers from different cultural environments? Specifically, does being surrounded by peers from more (or less) gender-equal backgrounds in higher education shape women's labor market behavior?

This section presents the empirical framework designed to answer this question. Identifying peer effects is inherently challenging due to the problem of selection or endogenous peer formation. Since students choose the universities and programs they apply to, peer groups are not randomly assigned. As a result, exposure to particular peer characteristics—such as the average level of gender equality in peers' home provinces—may be correlated with students' own unobserved preferences or motivations, which themselves influence labor market outcomes. This raises the classic issue of correlated effects, as defined in Manski (1993).

To address the selection issue, my identification strategy exploits within-degree variation in the geographic origins of peers across consecutive enrollment cohorts. This approach, first proposed by Hoxby (2000) to study the effects of peers' gender on educational outcomes, has become a standard approach in peer effects research.[28] The core idea is that

[27] A stronger relationship appears when using quartiles of male labor force participation (MLFP).

[28] A non-exhaustive list of related studies includes: Angrist and Lang (2004), Lavy and Schlosser (2011),

while students self-select into programs based on time-invariant characteristics - e.g. program quality and average peer composition - they cannot control the precise geographical composition of their entering cohort. This is particularly plausible in Italy, where student cohorts exhibit substantial year-to-year variation in regional composition due to large inflows from across the country. The key identifying assumption is that conditional on degree program fixed effects, year-to-year variation in the share of peers from high- versus low-FLFP provinces is as good as random—that is, it is uncorrelated with unobserved determinants of individual labor market outcomes. I provide several tests of this assumption in Subsections 5.2 and 7.1.

Practically, implementing this design requires longitudinal data to track how peer composition within Master's programs evolves over time. My dataset is uniquely suited for this purpose: it covers a large panel of Master's programs—spanning nearly the entire student population in Italy—across multiple enrollment cohorts from 2012 to 2016. This structure enables the analysis of how fluctuations in peer group composition—particularly in exposure to gender-equal norms—shape women's subsequent labor supply behavior.

5.1 The Empirical Model

The associated empirical model is:

$$Y_{idc} = \theta_d + \alpha_c + \gamma FLFP_{idc} + \delta^{FP}\overline{FLFP}^{FP}_{-i,dc} + \delta^{MP}\overline{FLFP}^{MP}_{-i,dc} + \varepsilon_{idc} \tag{2}$$

where i denotes a student enrolled in degree program d and cohort c. $\overline{FLFP}^{FP}_{-i,dc}$ and $\overline{FLFP}^{MP}_{-i,dc}$ represent the leave-one-out average FLFP in the province of origin of same-gender and opposite-gender peers, respectively, within the same degree and cohort. Formally:

$$\overline{FLFP}^{FP}_{-i,dc} = \frac{\sum_{j\neq i} FLFP_{jdc}}{n^{F}_{dc}-1} \text{ if female=1;} \qquad \overline{FLFP}^{MP}_{-i,dc} = \frac{\sum_{j} FLFP_{jdc}}{n^{M}_{dc}} \text{ if female=1;}$$

$$\overline{FLFP}^{FP}_{-i,dc} = \frac{\sum_{j} FLFP_{jdc}}{n^{F}_{dc}} \text{ if female=0;} \qquad \overline{FLFP}^{MP}_{-i,dc} = \frac{\sum_{j\neq i} FLFP_{jdc}}{n^{M}_{dc}-1} \text{ if female=0;}$$

Because the leave-one-out approach mechanically induces a negative correlation between a student's own FLFP and the average FLFP of their same-sex peers, I control for the FLFP in the student's own province of origin, $FLFP_{idc}$, or alternatively include province-of-origin fixed effects. The parameters of interest are δ^{FP} and δ^{MP}, which capture the effects of being exposed to female or male peers from provinces with one percentage point higher FLFP. While FLFP is the primary measure used here, the model is also estimated with alternative indicators introduced in Section 3.

Bifulco et al. (2011), Lavy et al. (2012), Black et al. (2013), Carrell et al. (2018), Brenøe and Zölitz (2020), Olivetti et al. (2020), Cattan et al. (2022), and Cools et al. (2022).

The panel structure of the data allows me to include degree fixed effects θ_d to control for time-invariant characteristics of programs—such as typical student intake profiles—and unobserved determinants of graduate outcomes. Cohort fixed effects α_c capture factors common to all students entering university in a given year. The error term ε_{idc} contains both individual- and degree-level random components. Standard errors are clustered at the degree level to account for potential correlation in students' outcomes within degrees. Primary outcomes include net monthly earnings, weekly hours worked, full-time employment status, and hourly wages. I also examine a range of additional labor market outcomes, such as occupational category, industry, geographic job location, and contract type. All estimations are conducted separately for male and female subsamples.

5.2 Validity of the Empirical Strategy

Threat to identification. The key identification assumption is that $\overline{FLFP}{-}i, dc^{FP}$ and $\overline{FLFP}{-}i, dc^{MP}$ are uncorrelated with time-varying unobserved factors that influence students' labor market outcomes, conditional on degree and cohort fixed effects. In other words, peer composition must evolve quasi-randomly over time within programs.

This assumption is credible in the context of Italian Master's programs, where most degrees are selective and admission is based on academic criteria—such as undergraduate GPA or entrance exam scores—and where enrollment is typically capped. In these programs, fluctuations in the geographic mix of students arise from variation in who meets the admission threshold each year, rather than from shifts in the programs themselves. Conditional on academic ability, changes in the peer group's regional composition are therefore plausibly idiosyncratic.

The concern is greater for non-selective programs, where admission is not restricted and changes in peer composition may reflect shifts in the applicant pool itself. To address this, I implement a data-driven screening strategy that flags and excludes programs exhibiting signs of non-random cohort variation—such as sharp changes in enrollment size or academic ability (see Subsection 7.1).

Other potential threats include policy changes that alter program size or admission criteria, regional labor market shocks that shift application patterns, or feedback loops whereby the composition of one cohort influences the next. I assess these risks in detail below and provide evidence that the identifying variation behaves as if random within programs over time.

Balancing tests for cohort composition. To detect selection on observables into peer groups, I perform several checks. To assess potential selection into peer groups, I conduct a series of balancing checks using predetermined student characteristics. I

regress a rich set of pre-entry covariates—unaffected by peer influence but potentially correlated with unobserved student traits—on the peer FLFP variables, following equation 2. These include prior academic performance (Bachelor's and high school grades) and family background indicators (parental education and occupation). As shown in Tables 15 and 16, none of the coefficients on peer FLFP are statistically significant, indicating no systematic relationship between peer composition and baseline characteristics.

I complement the baseline balancing tests with two additional strategies. First, I predict students' labor market outcomes—such as labor supply and earnings—based solely on background characteristics, including age, high school type, academic grades, parental citizenship, and fixed effects for parental education and occupation. I then regress these predicted outcomes on peer FLFP exposure using the main specification (equation (2)). The idea is to test whether students with stronger or weaker expected labor market performance, based on pre-determined traits, are systematically sorted into cohorts with more gender-equal peers. As shown in Table 4, predicted outcomes are not related to peer FLFP for either gender, suggesting that cohort-level variation in peer composition is orthogonal to background-based earnings potential. Second, I regress the two treatment variables—$\overline{FLFP}{-}i, dc^{FP}$ and $\overline{FLFP}{-}i, dc^{MP}$—on the full set of predetermined covariates, controlling for degree and cohort fixed effects, and conduct joint Wald tests of significance. The resulting p-values of 0.381 and 0.221 indicate that observables do not predict exposure to more or less gender-equal peers, reinforcing the assumption of quasi-random peer composition across cohorts.

Taken together, these findings indicate that the treatment variable is unlikely to be correlated with unobserved, time-varying factors influencing labor market outcomes. Following the framework of Altonji and Blank (1999), selection on observed characteristics can reasonably proxy for selection on unobservables, lending support to the identification strategy. Nonetheless, this does not completely rule out the influence of concurrent institutional changes, such as local labor market dynamics affecting cohorts. To address these concerns, I perform robustness checks (Section 7.1), including the addition of degree- and region-specific time trends and the exclusion of degrees with potentially non-random changes in size or composition, confirming the stability of the results.

5.3 Identifying Variation

A key requirement of the empirical strategy is sufficient variation in peers' geographic composition across cohorts within Master's programs. Table 5 shows descriptive statistics for average FLFP in peers' provinces of origin, before and after removing degree and cohort fixed effects. The raw standard deviation is 8.50 percentage points among female peers and 8.59 among male peers. After netting out fixed effects, residual variation remains

Table 4: Balancedness Of Predicted Labor Market Outcomes

Panel A. Female Sample

	(1) Pr(employed)	(2) Log(monthly earnings)	(3) Log(weekly hours)	(4) Pr(fulltime)
$\hat{\delta}^{FP}$	-0.000	-0.000	-0.001	-0.000
	(0.001)	(0.002)	(0.001)	(0.001)
$\hat{\delta}^{MP}$	-0.000	-0.000	0.002	0.001
	(0.001)	(0.002)	(0.001)	(0.001)
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	146,476	146,476	146,476	146,476
R-squared	0.119	0.246	0.239	0.273

Panel B. Male Sample

	(1) Pr(employed)	(2) Log(monthly earnings)	(3) Log(weekly hours)	(4) Pr(fulltime)
$\hat{\delta}^{FP}$	-0.000	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
$\hat{\delta}^{MP}$	0.001	0.001	0.002	0.001
	(0.001)	(0.002)	(0.001)	(0.001)
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	106,448	106,448	106,448	106,448
R-squared	0.204	0.259	0.316	0.324

Notes. OLS estimates of a regression of predicted labor market outcomes on: the average FLFP in the provinces of origin of female and male peers and the FLFP in the own province of origin. Regressions include cohort and degree (Master × university) fixed effects and follow the estimating equation 2 in the main text. All regressors are standardized, and standard errors are clustered at the degree level. Labor market outcomes are predicted separately for female and male students using regressions of actual labor market outcomes on predetermined covariates: age, high school type (10 categories), high school grade, Bachelor's grade, dummy variables for mother's and father's citizenship (Italian vs. non-Italian), fixed effects for parents' educational attainment (10 categories), and fixed effects for parents' occupations (12 categories).

sizable—1.86 and 2.13 percentage points, respectively.[29] While most variation reflects sorting across degrees, roughly 20–25% occurs within programs over time. This residual variation—arguably orthogonal to individual choice—is the source of identifying variation. Figure 9 shows its time-series evolution across a random sample of degrees.

Importantly, this magnitude is consistent with random allocation of students across cohorts. To validate this, I simulate 500 random assignments of students to degrees and cohorts, preserving the observed distributions of FLFP and program size. The simulated residual standard deviation of peer FLFP averages centers around 1.95 percentage points (range: 1.87–2.02), closely matching the empirical values. Figure 6 shows that deviations

[29]Statistics for other regional indicators are in Table 17.

Table 5: Raw And Residual Variation Of Peers' Characteristics

	Mean	SD	Min	Max
A: Avg FLFP In Province Of Origin Of Female Peers				
Raw Cohort Variable	49.65	8.50	29.87	66.66
Residuals: Net Of Degree And Cohort FEs	0.00	1.86	-13.80	10.79
B: Avg FLFP In Province Of Origin Of Male Peers				
Raw Cohort Variable	49.72	8.59	27.33	66.66
Residuals: Net Of Degree And Cohort FEs	0.00	2.13	-16.80	14.51

Notes. The table reports descriptive statistics for the average FLFP in the province of origin of female (Panel A) and male (Panel B) students within degrees, before and after removing degree and cohort fixed effects. The unit of observation is a degree-cohort pair, leading to a total of 7,160 observations.

from average program composition follow an approximately normal distribution, further supporting the quasi-random assignment of peers conditional on controls.[30]

Identifying variation and program's size. If variations in students' characteristics across cohorts within a degree program are truly random, then by the law of large numbers, cross-cohort fluctuations should shrink with program size. Figure 7 confirms this: residualized peer FLFP is more volatile in small programs (average cohort size < 22) than in large ones (70–410 students). Table 18 complements this pattern, showing that while raw FLFP variation is stable across size quintiles, residual variation declines steadily with program size.

6 Estimates of Peer Effects

This section presents estimates from the empirical model (2) on labor market outcomes of female and male students.

Female earnings and labor supply. Table 6 reports estimates of peer effects on log net monthly earnings, log weekly hours worked, log hourly wages, and an indicator for full-time employment (typically 40 hours/week) for female students. All regressors are standardized. The results show that exposure to female peers from higher-FLFP provinces increases women's labor supply along the intensive margin. The magnitude of these effects is substantial: a one standard deviation increase in $\overline{FLFP}^{FP}_{-i,dc}$ (8.50 percentage points) is associated with a 3.3% increase in weekly hours worked and a 1.9 percentage point rise in the likelihood of full-time employment (a 2.7% increase relative to the mean). This translates into a 3.7% increase in net monthly earnings.[31] These effects are economically significant: they account for roughly 33%–40% of the observed gender gap in these labor

[30] Analogous plots for other gender culture measures appear in Figure 8.

[31] Results are virtually identical when controlling for province-of-origin fixed effects instead of the student's own province-level FLFP (Table 19).

outcomes, and 45%–76% of the gap between women from low- vs. high-FLFP provinces. Importantly, peer FLFP has no effect on extensive-margin participation or survey response rates (Table 20), alleviating concerns about selection into the analysis sample.

Table 6: Estimates Of Peer Effects On Earnings And Labor Supply - Female Sample

	(1) Log(monthly earnings)	(2) Log(weekly hours)	(3) Pr(fulltime)	(4) Log(hourly wage)
$\hat{\delta}^{FP}$	0.037***	0.033***	0.019**	0.003
	(0.013)	(0.012)	(0.009)	(0.012)
$\hat{\delta}^{MP}$	-0.000	0.001	-0.002	-0.002
	(0.010)	(0.009)	(0.007)	(0.010)
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	69,645	69,645	69,645	69,645
R-squared	0.287	0.246	0.280	0.100

Notes. OLS estimates of a regression of women's earnings and labor supply one year after graduation on: the average FLFP in the provinces of origin of female and male peers and the FLFP in the own province of origin. Regressions include cohort and degree fixed effects (equation 2). All the estimates are done on the sample of women who are employed one year after graduation and with non-missing information on these variables. Standard errors clustered at degree level. All regressors are standardised.

Gender-specific peer effects. These findings underscore the presence of gender-specific peer effects among women. In particular, the positive effects on earnings and hours worked are entirely driven by variation in the geographical mix of female peers, while estimates of δ^{MP} are consistently close to zero, suggesting that exposure to male classmates from high-FLFP provinces has no impact on women's labor outcomes. Several mechanisms may explain this asymmetry. First, as shown earlier, women's labor supply is strongly correlated with FLFP in their province of origin, while men's outcomes show weaker links. Thus, increasing the share of female peers from high-FLFP areas likely raises the presence of classmates with norms and preferences favoring full-time work—a channel less relevant for men. If peer effects work through mechanisms such as (i) conformism or (ii) social learning, it is thus reasonable to expect limited influence from male peers.

Nevertheless, opposite-sex peers may affect women's labor market choices through other channels, particularly in settings where partnerships form between classmates (Bursztyn et al. (2017)). For instance, men from more gender-egalitarian regions may hold different expectations about their partners' employment, as suggested in Fernández et al. (2004). If student couples form within programs, this could create a pathway through which male peers' origins could affect women's choices. However, this explanation finds little empirical support: responses to my original survey (Section 10) indicate that the

share of couples formed within the same Master's program is low. A third explanation concerns the structure of social networks. As shown in Section 3, women are more likely to discuss career plans with female than male classmates—a pattern consistent with widespread evidence of same-gender homophily in social interactions and information sharing (McPherson et al. (2001), Currarini et al. (2009)).

Female occupational choices. Table 7 presents estimates of peer effects on the occupations and industries women enter one year after graduation. Each of the 20 occupations and 21 industries is classified along two dimensions—average monthly earnings and full-time employment share—and coded as "high-earnings" or "high-full-time" if it falls above the respective median. These four binary indicators serve as outcome variables in the analysis. The results in Columns 1–2 show that exposure to female classmates from high-FLFP areas significantly influences women's occupational choices. A one standard deviation increase in $\overline{FLFP}^{FP}_{-i,dc}$ raises the likelihood of entering a high-earnings occupation by 1.8 percentage points and a high-full-time occupation by 1.6 points—equivalent to 4.9% and 3.1% increases relative to their means. These effects are, as previously discussed, gender-specific. To assess whether occupational sorting explains the rise in labor supply, I re-estimate the model for weekly hours worked including occupation and industry fixed effects. The coefficient on δ^{FP} falls by roughly one-third but remains large and statistically significant, suggesting that changes in occupational composition account for only part of the peer effect. This aligns with prior evidence that occupational sorting explains less than one-third of the gender gap in labor supply.

Other job characteristics. While exposure to female peers from high-FLFP provinces influences women's labor supply, earnings, and occupational choices, it does not appear to affect sorting along other observable job dimensions, such as employer characteristics. For example, there is no effect on hourly wages (Table 6, Column 4), nor on the industry of employment. Table 21 presents estimates of the empirical model for additional job characteristics, including whether the employer is in the public or private sector and the type of employment contract (permanent, informal/no contract, or self-employment). None of these variables are significantly affected by peer exposure.

Absence of peer effects on male outcomes. Table 22 presents results for male students, serving as a placebo test. If the FLFP in a student's province of origin primarily reflects female-specific attitudes and preferences, we would not expect peers' FLFP backgrounds to influence men's labor supply or earnings—just as men's own outcomes are largely unaffected by these factors in their home province. While indirect spillovers (e.g., rising female aspirations affecting male behavior) are theoretically possible, the estimates

Table 7: Estimates of Peer Effects on Occupations and Industries - Female sample

	(1)	(2)	(3)	(4)	(5)
	Occupation		Industry		Log(weekly hours)
	High-earn	High-full-time	High-earn	High-full-time	
$\hat{\delta}^{FP}$	0.018**	0.016*	0.014	0.008	0.023**
	(0.009)	(0.009)	(0.010)	(0.009)	(0.011)
$\hat{\delta}^{MP}$	-0.004	-0.005	-0.003	-0.009	-0.000
	(0.006)	(0.007)	(0.007)	(0.006)	(0.009)
Occ. & ind. FE					✓
Degree FE	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓
Observations	68,216	68,216	68,419	68,419	69,645
R-squared	0.361	0.466	0.272	0.398	0.349

Notes. OLS estimates of regressions of types of occupations and industries one year after graduation on: the average FLFP in the provinces of origin of female and male peers and the FLFP in the own province of origin. The dependent variables in Columns (1) and (3) are constructed from the distribution of earnings across occupations and industries, respectively. Specifically, indicators of high-earning occupations (industries) are based on whether an occupation (industry) pays above-median earnings. The dependent variables in Columns (2) and (4) are constructed from the distribution of full-time jobs across occupations and industries, respectively. Specifically, indicators of high-full-time occupations (industries) are based on whether an occupation (industry) has above-median shares of full-time jobs. Regressions include cohort and degree fixed effects. In Column 5, I add occupation FEs (20 classes) and industry FEs (21 classes). All the estimates are done on the sample of women who are employed one year after graduation and with non-missing information on these variables. Standard errors clustered at degree level. All regressors are standardised.

show no effect on men's weekly hours or full-time employment. A small positive effect on hourly wages appears at the 10% level but vanishes with additional controls for other geographical indicators. The absence of peer effects among men implies that the observed peer-driven gains for women translate into a 21–40% reduction in gender gaps in earnings and labor supply.

Sensitivity to Alternative Measures of Gender Equality. In this subsection, I assess the sensitivity of the estimates to the various indicators of gender equality defined in Section 3. The empirical model now becomes:

$$Y_{idc} = \theta_d + \alpha_c + \Lambda Z_{idc} + \pi^{FP}\overline{Z}^{FP}_{-i,dc} + \pi^{MP}\overline{Z}^{MP}_{-i,dc} + \varepsilon_{idc} \tag{3}$$

where Z_{idc} denotes the gender equality measure in the student's province of origin, and $\overline{Z}^{FP}_{-i,dc}$ and $\overline{Z}^{MP}_{-i,dc}$ are the corresponding averages for female and male peers, respectively. Table 23 reports results for log(monthly earnings), with each column corresponding to a different proxy for gender equality. Column (1) replicates the baseline estimate using FLFP. Across all alternative measures, peer effects remain positive and statistically significant, with slightly larger estimates when proxies capture the labor market behavior

of younger women or recent female graduates—suggesting this group plays a particularly salient role. Peer effects based on female labor market behavior (Columns 1–6) range from 0.035 to 0.041. Measures reflecting firm preferences and historical female-to-male literacy gaps produce smaller, though still significant, estimates (0.016 and 0.029, respectively).

7 Robustness Checks

This section serves two main purposes: (i) to reinforce the credibility of the identification strategy, and (ii) to confirm that the estimated peer effects on women's outcomes are driven by peers' gender-related traits rather than omitted variables or confounding influences. To keep the discussion concise, I focus on peer impacts on log monthly earnings; results for other outcomes are similar and available upon request.

7.1 Robustness

Recall from equation (2) that the error term in students' earnings, ε_{idc}, decomposes into a degree-specific component, v_{dc}, capturing time-varying degree-level shocks, and an individual-specific residual, u_{idc}. Section 5.2 showed that peer variables $\overline{FLFP}^{FP}_{-i,dc}$ and $\overline{FLFP}^{MP}_{-i,dc}$ are uncorrelated with observed individual characteristics, suggesting they are orthogonal to u_{idc}. This subsection examines whether the identifying variation is also uncorrelated with v_{dc}. Potential threats include (i) changes in program-level characteristics, such as admission policies that affect cohort size or student ability, and (ii) regional labor market shocks that influence the outcomes of all students entering local labor markets.

Trends. Adding degree-specific linear time trends leaves the peer effect estimates large and highly significant (Table 24). Likewise, including region-specific linear trends (Table 25) produces stable results.

Non-random changes in peers' composition. Since I do not directly observe admission policies, I adopt a data-driven strategy to detect potential non-random changes in student composition. Specifically, I regress the size of each degree program on a linear time trend and flag degrees with a significant trend (p-value ≤ 0.10), which accounts for approximately one-quarter of programs. Re-estimating the baseline model on the subset excluding these flagged degrees yields results that remain significant and, in some cases, even stronger (Table 26).

Next, I examine whether degree programs experienced substantial cohort-level shocks in observable characteristics. I focus on three variables: (i) the average Bachelor's grade (student ability), (ii) the standard deviation of Bachelor's grades (ability dispersion), and

(iii) cohort size. To quantify volatility in these measures over time, I first residualize each variable by removing degree and cohort fixed effects, then compute:

$$Z_d^Y = \frac{1}{T_{max}} \sum_{t=1}^{T_{max}} \left| r_{dt}^Y \right| \tag{4}$$

where r_{dt}^Y is the residual obtained from regressing the cohort average of characteristic Y on degree and cohort fixed effects, and T_{max} is the number of cohorts observed per degree (equal to 5 for 92% of programs). I then normalize each Z_d^Y by the average value of Y across cohorts. Ranking degrees by this standardized measure and progressively excluding those with the largest shocks, I find that the results are highly robust: peer effect estimates remain statistically significant and often grow in magnitude (Table 27).

7.2 Sensitivity Analysis

This subsection evaluates the sensitivity of peer effect estimates to alternative sample restrictions, specifically examining whether results vary by program size and the proportion of students who completed their Bachelor's degree at the same university. Results are summarized in Table 28.

Cohort size. First, excluding degrees in the bottom decile of the cohort size distribution leaves results virtually unchanged, suggesting the estimates are not driven by noise in very small programs. Second, I split the sample at the mean program size (47 students). The results reveal that peer effects are concentrated in smaller programs: estimates are larger and more precise in this group, while in larger programs they are attenuated and less significant. This pattern aligns with prior evidence indicating that the cross-cohort variation is much smaller. Furthermore, larger programs may feature more fragmented social networks, reducing beneficial peer interactions across the entire cohort.

Proportion of students with Bachelor at the same institution. In programs where a substantial share of students completed their Bachelor's at the same institution, peer origins may vary less idiosyncratically due to shared academic trajectories. To address this, I exclude degrees where the majority of students hold a Bachelor's from the same institution (Column 6), finding that results remain robust. Restricting further to degrees in the bottom quartile by this measure (Column 7) yields even larger estimated effects, which remain statistically significant despite the smaller sample size.

Student attendance to classes. As a placebo test, I analyze students who reported working full-time throughout their Master's program and thus had limited class attendance (about 8.7% of the sample). This group is expected to have minimal peer inter-

action, thus lim1iting potential peer effects. Consistent with this, peer effects are strong among students with high attendance but absent for those with low attendance, confirming that peer influence operates through actual social interactions.

7.3 Which Peers' Characteristics Matter?

The positive effect of exposure to female classmates from provinces with higher FLFP raises the question of which peer characteristics are truly driving the results. This section explores whether the observed effects are primarily attributable to peers' attitudes or beliefs related to —or whether they reflect other individual or geographic traits that happen to correlate with FLFP.

Alternative individual peers' characteristics. I extend the baseline specification to control for seven additional peer-level variables. As shown in Table 29, the estimated effects remain stable, suggesting they are not confounded by other observable peer characteristics. In particular, adding proxies for peer academic ability—such as the share of peers with above-median Bachelor's grades or with a background from academic-track high schools (*licei*)[32]—does not attenuate the results. Likewise, including indicators of peers' socioeconomic status, such as the proportion with working mothers, college-educated parents, or parents in high-status occupations, does not affect the estimates. These results suggest that the peer effects are not attributable to differences in ability or socioeconomic background between students from higher- versus lower-FLFP provinces. Further, including program-level characteristics—like cohort size and the share of female students—has no impact on the findings, indicating that peer composition in terms of geographical origin does not capture broader shifts in cohort characteristics.

Alternative geographical characteristics. As previously noted, FLFP is highly correlated with other regional characteristics (Table 5), raising concerns that the baseline estimates might capture broader geographical factors—such as exposure to peers from more economically developed areas—rather than gender-specific features of their provinces of origin. To address this, I augment the model by adding controls for a range of additional geographical characteristics of peers' provinces, alongside FLFP. These variables reflect alternative place-based factors that may influence students' expectations and behavior, including economic conditions and demographic profiles.

Table 30 shows that the main results remain robust. In particular, cross-cohort variation in women's outcomes is not driven by shifts in the share of female or male peers

[32] Academic-track high schools (*licei*) prepare students for university studies and serve here as a proxy for school quality.

from larger urban municipalities or from regions with higher per capita income[33]. This robustness holds when controlling for economic activity in peers' provinces, measured by the share of firms with more than 50 employees and the share in the service sector (Columns 3 and 4). Similarly, adding controls for fertility rates and female educational attainment at the provincial level leaves the estimates largely unchanged (Columns 5–7). Lastly, while adding MLFP as a control reduces the precision of the estimates—due to its high correlation with FLFP—it does not significantly alter the point estimate. Moreover, when FLFP is included, MLFP has no significant association with women's outcomes. Finally, I run placebo regressions using each alternative variable in place of FLFP. As shown in Table 31, none of these measures are significantly associated with women's outcomes across cohorts. Taken together, these findings suggest that the estimates likely capture the effects of exposure to peers from more or less gender-egalitarian areas, rather than other non-gender-specific characteristics of their provinces.

8 Asymmetry in Peer Effects

The Linear-in-Means (lim1) model, presented in equation 2, assumes that a student's outcome is a linear function of the average background characteristics of her peers. While analytically convenient, this specification imposes strong restrictions on the structure of peer effects—most notably, it requires that their magnitude (δ^{FP} and δ^{MP}) remains constant across the distribution of student backgrounds. However, growing empirical evidence suggests that peer effects are often non-linear (Boucher et al. (2024)).[34] The distinction is not merely technical: the validity of the lim1 model carries meaningful implications for welfare analysis. If peer effects are nonlinear, targeted reassignments of students across peer groups may improve some students' outcomes without harming others. In contrast, if effects are truly linear, any such reassignment would leave average outcomes unchanged. In what follows, I investigate potential nonlinearities in peer effects.

To explore heterogeneity in peer effects, I estimate specifications that allow peer influence to vary according to FLFP in a student's birth province. Each student is assigned to a quartile based on the distribution of provincial FLFP rates within the sample. For each degree-cohort, I compute the share of female and male peers who originate from provinces with above-median FLFP, which I interact with a student's own FLFP quartile (first through fourth). I control for degree and cohort fixed effects throughout. The

[33]These variables are defined at the municipal level.

[34]Beginning with Hoxby and Weingarth (2005), a number of empirical studies have investigated these non-linearities, including Carrell et al. (2009), Hanushek and Rivkin (2009), Lavy et al. (2012), Imberman et al. (2012), Burke and Sass (2013), Booij and Leuven (2017), Feld and Zölitz (2017), Tincani (2024).

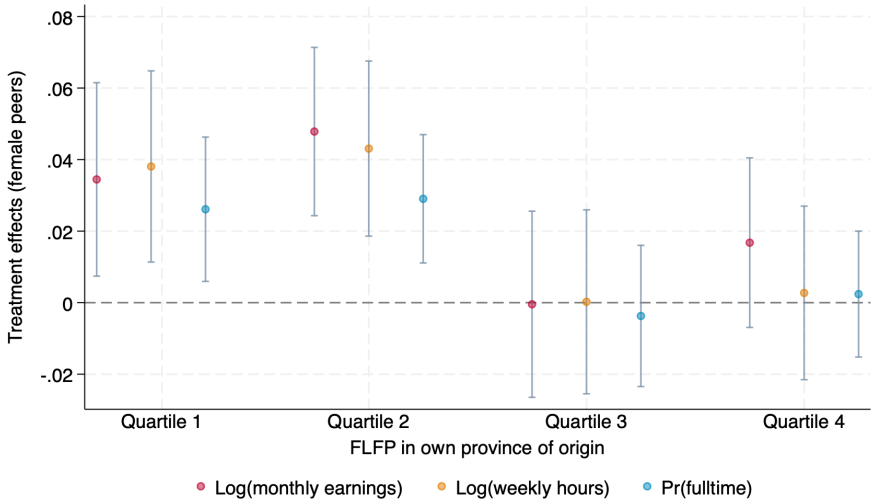
estimating equation is given by:

$$\begin{aligned} Y_{idc} = \theta_d + \alpha_c + \beta_1 + \beta_2 \text{Q2}_{idc} + \beta_3 \text{Q3}_{idc} + \beta_4 \text{Q4}_{idc} \\ + \gamma_1 \text{ShareAbm}^{FP}_{-i,dc} + \gamma_2 \text{ShareAbm}^{FP}_{-i,dc} \times \text{Q2}_{idc} \\ + \gamma_3 \text{ShareAbm}^{FP}_{-i,dc} \times \text{Q3}_{idc} + \gamma_4 \text{ShareAbm}^{FP}_{-i,dc} \times \text{Q4}_{idc} \\ + \alpha \text{ShareAbm}^{MP}_{-i,dc} + \varepsilon_{idc} \end{aligned} \tag{5}$$

Figure 3 illustrates the impact of increasing the share of female students from above-median FLFP regions on three outcomes: log(monthly earnings), log(weekly hours), and the probability of full-time employment (Pr(fulltime)), conditional on the student's own FLFP quartile. The results reveal a marked asymmetry in peer effects across the FLFP distribution. Specifically, students originating from the bottom two quartiles experience substantially larger gains compared to those from more egalitarian backgrounds. For example, increasing the share of egalitarian female peers by one standard deviation—equivalent to a 36 percentage point increase or roughly nine additional peers—raises the probability of full-time employment for women in the first and second FLFP quartiles by approximately 3 percentage points. In contrast, this same increase has no statistically significant effect for women in the third or fourth quartiles. Taken together, the evidence indicates that women from less-egalitarian regions benefit disproportionately from exposure to peers who come from high-FLFP areas, suggesting that reallocating such students into more egalitarian peer groups could raise average female earnings overall.

Horizontal and oblique influences in cultural transmission. The empirical model in equation 5 provides a framework to quantify the magnitude of peer effects relative to the influence of childhood background. Specifically, the coefficient β_4 captures the average difference in outcomes between women from the most egalitarian (Q4) and least egalitarian (Q1) birth provinces, evaluated at the mean share of female peers from high-FLFP regions. An increase in this peer share by one standard deviation adjusts the Q4–Q1 outcome gap to $\beta_4 + \gamma_4$, where γ_4 measures the extent to which peer exposure moderates the effect of background. Estimated coefficients for all quartiles are reported in Table 8. The results demonstrate that peer effects play a substantial role in narrowing disparities faced by women from less egalitarian regions. While the gap between Q2 and Q1 remains largely unaffected, exposure to egalitarian peers reduces the difference in hours worked between Q3 and Q1 by 65%, and between Q4 and Q1 by 58%. Regarding full-time employment, peer exposure fully closes the Q4–Q1 gap. Taken together, these findings suggest that peer interactions during college can significantly mitigate labor market disadvantages associated with growing up in less egalitarian environments.

Figure 3: Heterogeneous Effects by Student's Own Type



Notes. This figure plots the treatment effects of being exposed to a one standard deviation higher share of female peers from provinces with above-median FLFP, by quartile of FLFP in the student's province of origin. The dependent variables are log(monthly earnings), log(weekly hours), and the probability of full-time employment. These estimates are derived from a model where the share of female peers from provinces with above-median FLFP is interacted with the FLFP quartile of the student's province of origin, controlling for the share of male peers from provinces with above-median FLFP, as well as degree and cohort fixed effects. Standard errors are clustered at the degree level (equation 5).

Table 8: Magnitude Of Peer Effects Vs. Childhood Exposure

	(1) Log(monthly earnings)	(2) Log(weekly hours)	(3) Pr(fulltime)
$\hat{\beta}_2$	0.024***	0.037***	0.005
	(0.008)	(0.008)	(0.006)
$\hat{\gamma}_2$	0.013	0.005	0.003
	(0.008)	(0.008)	(0.007)
$\hat{\beta}_3$	0.059***	0.058***	0.030***
	(0.013)	(0.012)	(0.010)
$\hat{\gamma}_3$	-0.035***	-0.038***	-0.030***
	(0.013)	(0.012)	(0.010)
$\hat{\beta}_4$	0.060***	0.060***	0.023***
	(0.010)	(0.011)	(0.008)
$\hat{\gamma}_4$	-0.018	-0.035***	-0.024**
	(0.012)	(0.012)	(0.010)

Notes. The table presents estimates from the empirical model 5. Regressors have been standardised and standard errors are clustered at the degree level.

9 Mechanisms

Several mechanisms could plausibly underlie the peer effects documented above. In this section, I evaluate a set of candidate channels through which exposure to peers from more gender-egalitarian regions may influence labor market outcomes. I consider four broad categories: (i) migration networks, whereby peers may lower the costs of relocating to

higher-opportunity regions; (ii) human capital accumulation, if peer composition affects academic performance; (iii) shifts in preferences or attitudes, such as changes in career aspirations or gender norms; and (iv) information transmission, which I address in the next section.

9.1 What Peers Do Not Do

Human capital. A natural hypothesis is that peer composition affects academic performance, thereby improving labor market outcomes through enhanced human capital. To test this directly, I re-estimate the main specification using contemporaneous academic outcomes—GPA, final graduation grade, and delayed graduation status (*fuoricorso*)—as dependent variables. As shown in Table 32 (Panel A), the estimated effects are small and statistically insignificant across all measures, indicating that human capital accumulation is unlikely to be the primary channel driving the observed labor market improvements.

Migration networks through local labor markets. Peers may also influence labor market outcomes by shaping migration decisions. For example, exposure to students from other regions could expand information about job opportunities or reduce mobility costs via cohort-based social ties. To test this, I examine whether peer composition affects women's geographic mobility, measured by the FLFP level in the province of employment and indicators for whether the student migrates away from her province of birth or study. Results, presented in Table 32 (Panel B), reveal no significant relationship between peer origins and migration decisions. These findings suggest that access to broader migration networks is not a key driver of peer effects.

Networks. Another possibility is that peers facilitate access to better jobs through direct referrals or other labor market connections. Although firm-level identifiers are unavailable—precluding a direct test of referral-based explanations—I implement an indirect test exploiting variation in local student composition. The intuition is as follows: if peers from the university's province (i.e., local students) are more embedded in local labor markets through family or other connections, they may be more likely to share job information or offer referrals to non-local students. Approximately 70% of students remain and work in their region of study, making this a plausible channel. However, controlling for the share of local female and male peers in the baseline specification (Table 33) leaves the estimates largely unchanged. In fact, the peer coefficients increase slightly in magnitude, possibly reflecting a weakly negative effect of local peer presence on women's labor market outcomes. These patterns suggest that labor market referrals are unlikely to be the principal mechanism behind the observed peer effects.

9.2 What Peers Do: Shifts in Preferences and Social Learning

The central hypothesis is that female students from different provinces bring distinct norms and expectations about women's roles in the labor market—norms that may be transmitted through peer interactions. Testing this mechanism requires data capable of capturing shifts in women's preferences and beliefs within their social environment. To this end, I combine data on students' job-search preferences, collected via the pre-graduation survey, with evidence from a newly conducted survey.

I begin with students' self-reported job preferences, collected through a standardized institutional survey administered shortly before graduation (see Section 2.2 for details). Students rank the importance of various job attributes on a scale from 1 (low) to 5 (high). I construct two standardized indices: one for pecuniary job attributes (e.g., salary, career advancement) and one for temporal flexibility (e.g., flexible hours, time for leisure).[35] Each index is the unweighted average of the relevant attribute scores, standardized for interpretability. Additionally, I create a binary indicator for students who assign the highest possible importance to a job's social utility—a dimension with significant gender variation that has received limited attention. Using these measures as dependent variables in the empirical model, results in Table 34 show that exposure to peers from more gender-egalitarian regions alters women's valuation of job attributes. A one standard deviation increase in peers' gender culture leads to a 2.7% of a standard deviation reduction in preference for hours flexibility and decreases the likelihood of assigning maximum importance to a job's social utility by 1.2 percentage points—a 3% decline relative to the mean.

10 Evidence from a New Data Collection

To further investigate the mechanisms underlying my findings, I designed a novel survey with three objectives: (1) to explore variations in women's beliefs based on their childhood exposure to female labor force participation; (2) to assess the influence of these beliefs on job acceptance decisions; and (3) to examine how these beliefs are updated over time.

Design. While a growing body of research has documented the intergenerational persistence of cultural norms—often using the epidemiological approach based on ancestral culture—these studies typically remain agnostic about the specific beliefs driving this persistence.[36] This survey contributes to filling this gap by directly eliciting a broad set of be-

[35] This approach follows methodologies used in studies of gender differences in job preferences, such as Wiswall and Zafar (2018), Mas and Pallais (2017), and Eriksson and Kristensen (2014).

[36] One exception is Bursztyn et al. (2020), which identifies biased second-order beliefs among men—regarding the social acceptability of women working outside the home—as a key constraint on female labor force participation in Saudi Arabia.

liefs and expectations potentially relevant for women's labor supply decisions. The survey was initially designed to capture attitudes and social norms related to gender roles, as well as expectations regarding fertility and motherhood-related career interruptions (so-called *child penalties*). However, insights from a prelim1inary qualitative phase—consisting of 25 in-depth interviews with students from various universities—highlighted additional, previously underexplored considerations. In particular, respondents from less egalitarian regions frequently mentioned a perceived scarcity of full-time job opportunities for women, often attributed to employers' assumptions about future childcare responsibilities. Motivated by these findings, the final version of the questionnaire was expanded to include measures of labor market expectations, such as beliefs about job availability and anticipated employer discrimination. The survey was structured to track these beliefs over time.

10.1 Survey Administration

The survey was conducted among graduate students enrolled at the University of Bologna, the largest university in the country, accounting for approximately 7% of all national graduates. Importantly, it attracts students from diverse cultural backgrounds, with 88.8% and 69.6% of participants coming from different provinces and regions, respectively.

To construct the analysis sample, I randomly selected a subset of Master's programs and, within each, randomly chose one first-semester course from the first year and one from the second year. Students attending these courses were invited to participate in the survey. The survey was administered in person during class time. Specifically, with lecturers' consent, I visited each class—typically during the first or last 15 minutes—and invited students to voluntarily complete a 10-minute questionnaire via their mobile devices using the SurveyMonkey platform. Prior to administration, I provided general information about the study.[37] To encourage participation, students were offered entry into a lottery with three prizes, each consisting of €100 gift cards.[38] The response rate among attending students was approximately 97%.[39] Importantly, students were not informed in advance about the survey administration to ensure that attendance during the intervention was exogenous to the survey, thereby mitigating selection concerns.

The survey took place between November 2023 and February 2024. I chose to run the survey 3-4 months after the start of the academic year to strike a balance between

[37]Students were informed that the questionnaire focused on their beliefs and labor market expectations as part of a study on post-college career decisions. To avoid priming, the connection to peer influence or gender inequalities was not disclosed.

[38]The gift cards were generic and redeemable across multiple providers to minimize selection bias related to gift choice.

[39]Self-reported attendance data from the AlmaLaurea survey indicates that around 77% of students attend classes regularly.

students being able to give informed responses to the questions—especially about the program's social environment— and learning of students in the first year being not yet complete. A total of 899 students from 34 Master's programs participated in the survey. Among them, 535 identified as women, 348 as men, and 13 as non-binary. The sample included 571 students in their first year and 322 in their second year. This disparity is attributed to the curriculum structure, with mandatory courses mainly offered in the first year. Consequently, the second-year cohort tends to be smaller due to the greater flexibility in choosing optional courses.

10.2 Sample Selection and Description

I exclude from the sample students participating in the Erasmus program or enrolled in a Bachelor's program (less than 1%), as well as those with missing information on their country or province of origin (5.8%). The final sample comprises 490 female students, with 319 in the first year and 171 in the second year of their Master's programs.

Summary statistics for the full sample and subgroups defined by the FLFP rate in students' province of origin are presented in Table 35. Compared to the main sample, this sample overrepresents students from higher socioeconomic backgrounds, as indicated by a greater share of parents with university degrees, and includes more students from provinces with higher FLFP rates. Additionally, the sampled programs have a larger proportion of students who migrated from other provinces or regions. Finally, the distribution of fields of study differs: disciplines such as engineering, architecture, healthcare, and psychology are absent, while the humanities are overrepresented.

A comparison of women from high- and low-FLFP provinces of origin reveals differences in the role models present within their families. Students from low-FLFP provinces are more likely to have fathers with higher education levels than their mothers, whereas the reverse is true for students from high-FLFP areas. Additionally, mothers in low-FLFP provinces are more likely to have experienced significant career interruptions—so-called *child penalties*—during their children's early years. Despite these background differences, the two groups are similar in several important respects. Just under 50% of students in both groups report being in a couple, though only a small fraction have partners within the same Master's program. Furthermore, their fertility expectations and job-search intentions are broadly comparable.

10.3 Expectations About The Job Offer Distribution

This section investigates how students' expectations about the job offer distribution vary by background and are shaped by learning. The hypothesis is that women raised in regions with weaker female labor market conditions may hold more pessimistic beliefs

about the frequency of job offers, particularly with regard to full-time versus part-time work. To test this, I elicit students' expectations about two key parameters of a job search model: (i) the overall arrival rate of job offers, and (ii) the relative frequency of part-time versus full-time offers. Beliefs are collected using the hypothetical scenarios described in Box 10.3. The design builds on a random search framework, which provides a tractable way to identify the primitives of interest.[40]

Expectations are elicited by fixing the number of job applications at ten, which allows for isolating perceptions about the likelihood of receiving job offers, abstracting from heterogeneity in expected search effort. Restricting the hypothetical applications to jobs in the student's field of study narrows the occupational set and enhances comparability across respondents.

Since realized labor market outcomes are not observable for this prospective sample, I also collect students' stated intentions to accept part-time job offers. Following the approach of Wiswall and Zafar (2021), these intentions are measured using a stated probabilities method rather than a discrete choice format. This technique captures the uncertainty students face when reporting their likely decisions.[41]

[40] Although the random search model abstracts from endogenous application behavior, its insights extend to directed search frameworks, in which beliefs about offer probabilities influence both application targeting and search effort. In both settings, differences in beliefs can shape behavior and contribute to unequal outcomes.

[41] A discrete choice model is a lim1iting case of the stated probability framework—one in which individuals have no uncertainty, and would assign a probability of exactly 1 (certain acceptance) or 0 (certain rejection) to the job offer. However, the data reject this assumption: only 4.83% of students report a probability of 1, and fewer than 1% report a probability of 0.

Elicitation of Job Offer Arrival Rates

1. *Consider the following scenario: you have graduated from the Master's program in which you are currently enrolled and you start searching for a job. You submit 10 applications to positions aligned with your field of study. When applying, you don't know the specific working conditions—such as the monthly salary or whether the contract is part-time or full-time*[a].

- Out of these 10 applications, how many job offers do you expect to receive? ($\boldsymbol{\alpha}$) Provide your answer on a scale from 0 to 10.

- You receive your first job offer. What do you believe is the probability that the employer will offer you a part-time contract (less than 28 hours/week)? ($\boldsymbol{\gamma}$) Provide your answer on a scale from 0 to 100.

2. *While waiting for responses to your applications, an employer contacts you and offers a part-time position (28 hours/week) with a net monthly salary in line with your expectations. You must decide whether to accept the offer or turn it down and wait for responses from the other applications.*

- What is the probability that you would accept this part-time job offer? Provide your answer on a scale from 0 to 100.

[a]Note that in Italy, 91% of online job postings do not include salary or salary ranges, and precise information about working hours is often limited (Burning Glass data)

Asymmetries in baseline beliefs. Table 9, Panel (a), presents an analysis of students' baseline beliefs, elicited during the first year of their program-prior to substantial peer interaction-to capture initial heterogeneity shaped by pre-college environments. The table compares beliefs between students from provinces with below- versus above-median FLFP. Each belief (rows) is regressed on a binary indicator for high-FLFP origin, controlling for field of study fixed effects. The estimates reveal systematic differences in expectations by province of origin. First, women from low-FLFP provinces expect marginally fewer job offers: among ten submitted applications, they anticipate receiving 3.21 offers on average, compared to 3.52 among their high-FLFP counterparts, though this difference is not statistically significant. More notably, a substantial and significant gap emerges in their expectations regarding the proportion of part-time job offers. Women from low-FLFP areas expect a 6.45 percentage point higher likelihood that an offer will be part-time rather than full-time—equivalent to a 12.6% increase relative to the high-FLFP group. Consistent with these expectations, they are also 7 percentage points more likely to report that they would accept a part-time offer, a difference of similar magnitude (12%). These asymmetries persist after controlling for students' background characteristics (e.g., age, parental education), job search intentions, and expected job location, as shown in Table 36.

In addition, field-of-study fixed effects mitigate concerns that the differences reflect sorting into distinct occupational tracks.

Table 9: Baseline and Updated Beliefs on the Job Offer Distribution

	Below-med FLFP		**Above-med FLFP**		
	Pred	SE	Pred	SE	P-value
a. Baseline Beliefs (T=0)					
α: Expected arrival rate of job offers (%)	32.06	1.77	35.24	1.24	0.15
γ: Expected % of part-time job offers	57.64	2.29	51.19	1.61	0.02
Prob. to accept part-time job offer	67.43	2.04	60.39	1.44	0.01
b. Updated Beliefs (T=1)					
α: Expected arrival rate of job offers (%)	32.20	2.17	32.19	1.73	1.00
γ: Expected % of part-time job offers	52.47	2.90	50.70	2.31	0.64
Prob. to accept part-time job offer	62.48	2.81	62.37	2.23	0.98

Notes. This table presents predictions from a linear regression model, where the dependent variable is regressed on an indicator for whether the FLFP in the birth province is above or below the median, along with fixed effects for the field of study. Each row represents a different regression, with the dependent variable specified in Column 1. The last column provides the p-value for the difference between the two groups. In Panel (a), the sample consists of all first-year female Master's students (319), and in Panel (b), it includes all second-year female Master's students (164). Between 60% and 65% of the students in the two cohorts are from provinces with above-median FLFP.

Beliefs updating. Panel (b) of Table 9 analyzes how beliefs evolve over time by examining responses from second-year students. Overall, the results indicate convergence in beliefs across students from low- and high-FLFP provinces, consistent with a process of learning. In particular, the initially large gap in expectations about the likelihood of receiving a part-time job offer narrows by more than 70% between the first and second years. Further evidence supporting the learning interpretation comes from changes in the within-field dispersion of beliefs. Across degree programs, the standard deviation in students' expectations about part-time job offers is 24.28 in the first year, declining by over one-third in the second year. Importantly, belief updating is strongly asymmetric, mirroring the heterogeneity in peer effects. Women from low-FLFP provinces revise their expectations downward by more than 5 percentage points—a 9% decrease—while women from high-FLFP provinces exhibit no significant change. This asymmetry in updating could be consistent with prior differences in information sets. Students from low-FLFP areas likely form their initial beliefs based on labor markets that differ substantially from the ones in which they now expect to work, as implied by their intended job location (Table 35), while such discrepancy is less pronounced for their high-FLFP counterparts. While the data do not permit a causal identification of peer effects, the stark downward revision among low-FLFP students—coupled with the stability among their high-FLFP peers—suggests that peer-driven information transmission is a plausible mechanism behind belief updating.

10.4 Beliefs and Job Search: an Illustrative Model

How does heterogeneity in beliefs translate into differences in economic outcomes? To illustrate this relationship, I develop a stylized job search model in the spirit of McCall (1970), in which risk-neutral female graduates search for their first post-graduation job. The model abstracts from geographical origin in the baseline setup, allowing for a clean exposition of the core mechanism. I later introduce heterogeneity in key parameters to capture differences between women from high- and low-FLFP provinces, with a focus on implications for part-time job acceptance.

Model setup. Consider an economy where three states exists: an individual can be unemployed, employed in a part-time job or employed in a full-time job. Both part-time (P) and full-time (F) jobs involve fixed weekly hours. I denote the number of hours in a part-time job as $h^P = \theta h^F$, with $\theta < 1$. Time is discrete, and all individuals discount the future at a constant rate $\beta \in (0, 1)$. Individuals are risk-neutral and derive utility solely from income. Their preferences are represented by a simple linear utility function over consumption, u(c) = y, implying that they seek to maximize expected lifetime labor income. I abstract from other sources of income, so that instantaneous income is given by:

$$y = \begin{cases} y^F & \text{if employed in full-time job} \\ y^P & \text{if employed in part-time job} \\ b & \text{if unemployed} \end{cases}$$

Unemployed individuals receive an instantaneous utility of b, which reflects any income or value associated with not working, such as the pecuniary value of leisure or unemployment insurance (UI) benefits. y_P and y_F denote the total per-period income associated with part-time and full-time employment, respectively. For simplicity, I normalize the number of hours in a full-time job to one, so that $y_F = w$ and $y_P = \theta w$.

Each period, unemployed job seekers receive job offers with probability α^*. A fraction γ^* of these offers are part-time positions. Each job offer includes a wage drawn from a distribution F(w), which has support and non-zero density on $[w_{\min}, w_{\max}]$. To simplify the analysis, I assume that the wage distribution is the same for part-time and full-time offers. Upon receiving a job offer, individuals decide whether to accept the offer and exit unemployment, or reject it and continue searching while enjoying the value of leisure b. I assume that employment—both part-time and full-time—is an absorbing state, i.e. there is no job destruction and no on-the-job search. I further assume that the environment is stable, i.e. that the arrival rates of full-time and part-time job offers

do not change over the course of the search spell. Individuals are infinitely lived and, therefore, the model is stationary. Throughout the analysis, I use an asterisk * to denote true, objective probabilities of job offer arrival. This notation distinguishes actual labor market parameters from individuals' subjective beliefs, which may differ from the truth.

Workers' beliefs. I begin by assuming that workers make decisions under potentially limited information regarding job offer arrival rates. In particular, workers may not know the true per-period probability of receiving a job offer, α^* or the true proportion of part-time job offers, denoted by γ^*. Let α_t and γ_t represent the worker's subjective beliefs about these parameters. Beliefs are biased if $\alpha_t \neq \alpha^*$ or $\gamma_t \neq \gamma^*$. While beliefs potentially evolve over time due to learning, in this version of the model I abstract from this possibility and assume that α and γ are not time-varying. Workers take their decisions on whether to accept job offers based on their subjective beliefs α and γ. I abstract away from other potential biases in beliefs, for example on the wage offer distribution F(w), that I assume to be commonly known to all individuals.

Perceived values of employment and unemployment. I now characterize the perceived flow values of unemployment and employment.[42] For a worker with beliefs α and γ, the perceived value of unemployment equals

$$\begin{aligned} U(\alpha,\gamma) = b + \beta\alpha\Bigg[\gamma \int_{y_P} \max\{V(y_P), U(\alpha,\gamma)\}\, dG(y_P) \\ + (1-\gamma)\int_{y_F} \max\{V(y_F), U(\alpha,\gamma)\}\, dG(y_F)\Bigg] \\ + \beta(1-\alpha)U(\alpha,\gamma) \end{aligned} \tag{6}$$

The values of part-time and full-time employment at wage w are respectively

$$V(y_P) = y_P + \beta V(y_P) \rightarrow (1-\beta)V(y_P) = \theta w \tag{7}$$

$$V(y_F) = y_F + \beta V(y_F) \rightarrow (1-\beta)V(y_F) = w \tag{8}$$

Reservation wages. A job-seeker's decision to accept a job offer is determined by the reservation wage property: each job offering wages above the reservation value is accepted. The job seeker determines her reservation wage in order to maximize their perceived continuation value at any point during the search spell. I define the reservation earnings, $R(\alpha,\gamma)$, as the total per-period income at which a job seeker is indifferent

[42] These values are "perceived" in the sense that they are based on the worker's subjective beliefs about the arrival rates of job offers rather than the true underlying probabilities.

between accepting a job and remaining unemployed. The resulting expression for the reservation earnings equals

$$V(R(\alpha,\gamma)) - U(\alpha,\gamma) = 0 \rightarrow R(\alpha,\gamma) = (1-\beta)U(\alpha,\gamma) \tag{9}$$

Because part-time and full-time jobs differ in the number of working hours, the reservation earnings condition expressed above is verified for two different reservation wages, separately for the two job types. I define the reservation wages for part-time and full-time jobs as $w_{R,P}(\alpha,\gamma)$ and $w_{R,F}(\alpha,\gamma)$. The expressions are

$$w_{R,P}(\alpha,\gamma) = \frac{R(\alpha,\gamma)}{\theta} \quad \text{and} \quad w_{R,F}(\alpha,\gamma) = R(\alpha,\gamma) \tag{10}$$

Any part-time or full-time job offering wages above these values is accepted. Reservation wages are determined based on workers' beliefs regarding α^* and γ^*, as illustrated in the following propositions.

Proposition 1. *Ceteris paribus, reservation wages are increasing in beliefs α.*
Proposition 2. *Ceteris paribus, reservation wages are decreasing in beliefs γ.*

The proofs are contained in Appendix A.

Heterogeneous beliefs and model's predictions. Although all individuals face the same objective job offer arrival rates, I allow for heterogeneity in beliefs. Let (α_L, γ_L) and (α_H, γ_H) denote the subjective beliefs held by women from low- and high-FLFP regions, respectively. Empirical evidence from the previous section indicates that women from low-FLFP provinces expect both fewer job offers and a higher proportion of part-time opportunities.[43] Formally:

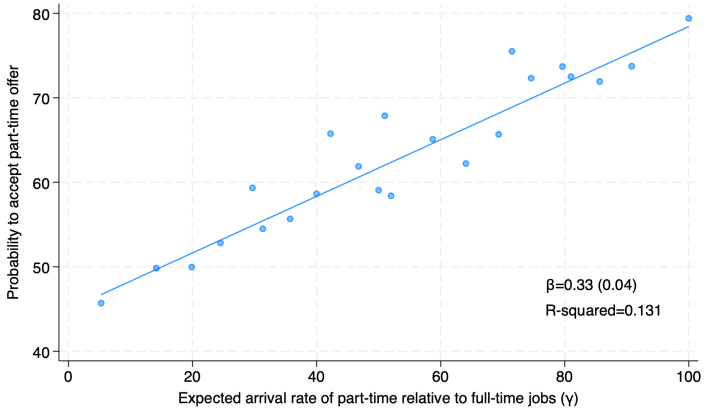
$$\alpha_L < \alpha_H \quad \text{and} \quad \gamma_L > \gamma_H \tag{11}$$

By Propositions 1 and 2, these beliefs imply lower reservation earnings among women from low-FLFP regions, leading to a greater likelihood of accepting part-time employment. Figure 4 illustrates a strong relationship between students' subjective expectations about the prevalence of part-time job offers and their willingness to accept such offers. Estimates from a simple linear regression indicate that a one standard deviation increase (23 percentage points) in the expected probability of receiving a part-time offer results in an approximately 8 percentage point increase in the acceptance rate of part-time jobs,

[43] A discussion on job-finding probabilities is presented in Appendix A.

representing more than a third of the standard deviation in the sample, and this is robust to the inclusion of field fixed effects (Table 37).

Figure 4: Acceptance of part-time jobs and expected share of part-time job offers



Notes. This figure presents binned scatter plots of the probability of accepting a part-time job against the expected arrival rate of part-time relative to full-time job offers (γ). One observation represents a student in the sample. β is the estimated coefficient from a simple linear regression of the intended probability of accepting a part-time offer on the expected share of part-time job offers.

10.5 Fertility and Gender Attitudes

Expectations about fertility and future child penalties. In Italy, child penalties-reductions in labor supply following childbirth-vary sharply by region (Casarico and Lattanzio (2023)). These regional disparities may shape women's beliefs about their own future trajectories: those from less gender-equal contexts may expect children at younger ages or anticipate larger employment losses associated with motherhood, and may respond by selecting into more flexible jobs in anticipation of motherhood (as in Adda et al. (2017)). This section tests whether women from high- and low-FLFP areas hold systematically different expectations about fertility timing and the career costs of children (elicitation is described in Box 10.5).

Table 38 presents the main results. At baseline, women from low-FLFP provinces are slightly less likely to expect to have children in the future and anticipate doing so at a marginally later age compared to their peers from high-FLFP provinces. More importantly, they are less likely to foresee reductions in working hours due to motherhood and more likely to expect to remain employed full-time during the early years of parenthood. This pattern holds across both unconditional expectations (Scenario 1) and conditional expectations in the presence of full-day childcare near their residence (Scenario 2). For both groups, childcare availability significantly shifts anticipated labor supply: the share of women expecting to work full-time increases by 43%–58% with access to full-day childcare. One year later, both groups revise their expectations upward, especially under the childcare-available scenario. Approximately 80% of women in each group now expect

to work full-time during the early years of motherhood. Two things emerge from this analysis. First, women from low-FLFP areas do not anticipate higher career costs of motherhood. This may reflect misperceptions about the magnitude of child penalties (as in Kuziemko et al. (2018)), positive selection in the sample, or shifts in the magnitude of child penalties themselves. Second, in contrast to the asymmetric updating observed for job offer beliefs, expectations related to motherhood and future employment evolve symmetrically across both groups, which mitigates concerns that students from high-FLFP areas are generally more resistant to belief updating.

Elicitation of Fertility Expectations

1. Would you like to have children in the future? *Yes / No / Don't know / Already have*
2. At what age do you expect to have your first child?
3. Expected labor supply at motherhood:
   - ***Scenario 1***. *Suppose that your partner is earning enough to support your family. What do you think you will do when your child is young (0–2 years)?*
     Answer: *No work / Work part-time / Work full-time*
   - ***Scenario 2***. *Suppose that your partner is earning enough to support your family and that in the area you live a full-day place in childcare is available to you. What do you think you will do when your child is young (0–2 years)?*
     Answer: *No work / Work part-time / Work full-time*

Gender attitudes. The survey also elicits women's attitudes toward employer discrimination and societal expectations regarding gender roles. Respondents were asked to indicate their agreement with two statements: "Employers prefer to hire men for full-time jobs" and "A woman is negatively judged in society if she is too ambitious," using a Likert scale ranging from strongly disagree to strongly agree.

Table 39 compares responses across students from provinces with above- and below-median FLFP, controlling for field of study. Several patterns emerge. First, in both groups, a majority of women perceive gender-based discrimination in hiring and believe that ambitious women face social scrutiny. However, at baseline, women from low-FLFP areas are more likely to agree or strongly agree with these statements, indicating more traditional or pessimistic views. Over time, attitudes show modest changes. Among low-FLFP students, disagreement with the statement on employer discrimination becomes more common, yet the share of respondents who strongly agree also increases in both groups. Furthermore, gaps in perceived social judgement appear to widen. Specifically, students from low-FLFP areas become more likely to agree that ambitious women are judged negatively, whereas those from high-FLFP areas display increases at both ends of

the scale—greater disagreement, but also a rise in strong agreement.

10.6 Discussion

Overall, these survey findings provide novel insights into potential drivers of *cultural persistence* and plausible mechanisms behind peer effects beyond those previously discussed. A key takeaway is that the broader social environment in which individuals are raised—even beyond family influence—shapes women's beliefs about labor market opportunities and their second-order beliefs regarding gender roles. Women from less gender-equal areas perceive ambition as less socially acceptable and hold more pessimistic beliefs about their career prospects. While research on belief formation about labor market outcomes is still emerging (Spinnewijn (2015)), these findings suggest that such expectations are shaped early by observing local labor market conditions and may persist even after individuals migrate.[44] Importantly, this highlights the role of information frictions alongside more commonly cited factors—such as attitudes and preferences—in perpetuating norms around female labor market participation. A second key observation concerns the divergent evolution of beliefs. While expectations about job offer arrival rates appear responsive to new information, potentially through peer learning, gaps in perceived gender roles remain more persistent over time. This aligns with prior evidence (e.g., Giavazzi et al. (2019)) showing that views on women's societal roles tend to be particularly resistant to change.

11 Conclusions

The persistence of traditional gender roles, reflected in the unequal participation of men and women in paid work, remains a key barrier to gender convergence in the labor market. While many studies have documented the long-run persistence of gender norms, much less attention has been given to understanding the factors that shape their evolution.

This paper provides new evidence that exposure to university classmates born in more gender-equal regions shapes women's labor supply and occupational choices, operating through both changes in job-search preferences and social learning. Italy offers a compelling context for studying cultural norms, given its exceptionally wide geographic variation in gender equality, with female-to-male labor force participation (FLFP) rates ranging from 44% to 86% across provinces. Due to substantial internal mobility, Italian universities bring together students from regions with stark differences in gender equality, who, according to novel data I collected, systematically differ in their labor market expectations and beliefs on gender roles. Because Master's programs are typically small, they exhibit

[44] Although beyond this paper's scope, the persistence of such beliefs among migrants may also help explain other enduring labor market disparities, such as differences between migrants and natives or between movers from high- versus low-opportunity areas (Chetty and Hendren (2018)).

substantial cohort-by-cohort variation in the geographic origins of students, generating quasi-random variation in peer exposure to gender norms that I exploit for identification. I leverage rich administrative data on the peer composition of over 1,500 Master's programs between 2012 and 2016, linked to early-career labor market outcomes and detailed information on students' family backgrounds, education, and job-search preferences.

I find that exposure to female classmates from provinces with higher female labor force participation (FLFP) significantly increases women's likelihood of entering full-time employment, partly through greater sorting into occupations where full-time work is more prevalent. In contrast, men's outcomes remain unaffected, implying that peer exposure can substantially narrow early-career gender gaps—by 21 to 40%, depending on the outcome. Crucially, the effects are not driven by broader regional characteristics: they are robust across a range of gender-specific indicators and fade or disappear when using non-gender-related measures, such as per-capita income or economic activity.

The beneficial impacts of peer exposure are concentrated among women from provinces with below-median FLFP. This asymmetry is striking: a 36 percentage point increase in the share of peers from high-FLFP areas closes up to 65% of the labor supply gap between women from low- and high-FLFP regions, suggesting that peer exposure can partly offset the lasting influence of limited female role models during childhood. These findings imply that policies fostering geographic diversity in higher education could be an effective lever for shifting gender norms and advancing gender equality.

To understand the mechanisms, I combine several new data sources, including a novel survey that I designed to track students' beliefs. Two key channels emerge. First, exposure to peers from more gender-equal regions lowers the value that women place on non-pecuniary job attributes-such as flexibility and leisure- when making career decisions. Second, peer interactions appear to reduce information frictions: women from low-FLFP areas begin their studies with more pessimistic beliefs about their chances of receiving full-time job offers, even when targeting the same labor markets as their high-FLFP peers. These beliefs converge over time, driven by asymmetric updating among women from less gender-equal backgrounds. In contrast, beliefs about traditional gender roles prove more persistent, suggesting that expectations about opportunities are more malleable than deeper cultural attitudes.

Overall, the latter findings point to information frictions as a novel and policy-relevant mechanism behind the persistence of gender norms. Low-cost interventions that improve access to accurate labor market information-particularly for women from more traditional backgrounds- could help shift beliefs and aspirations in ways that meaningfully reduce gender disparities. Further research is needed to identify how such information treatments could replicate the effects of peer-based social learning.

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APPENDIX

A Proofs

Proof of Proposition 1

Proof. The perceived value of unemployment can be rewritten as

$$(1-\beta)U(\alpha,\gamma) = b + \beta\alpha\Big[\gamma\int_R^{\bar{y_P}}(V(y_P)-U(\alpha,\gamma))\,dG(y_P) + (1-\gamma)\int_R^{\bar{y_F}}(V(y_F)-U(\alpha,\gamma))\,dG(y_F)\Big]$$

Using the reservation earnings rule and plugging the values of employment, this becomes

$$R(\alpha,\gamma) = b + \beta\frac{\alpha}{1-\beta}\Big[\gamma\int_R^{\bar{y_P}}(y_P-R(\alpha,\gamma))\,dG(y_P) + (1-\gamma)\int_R^{\bar{y_F}}(y_F-R(\alpha,\gamma))\,dG(y_F)\Big]$$

Rearranging yields

$$R(\alpha,\gamma) = b + \beta\frac{\alpha}{1-\beta}\Big[\gamma\int_R^{\bar{y_P}}(y_P-R(\alpha,\gamma))\,dG(y_P) + (1-\gamma)\int_R^{\bar{y_F}}(y_F-R(\alpha,\gamma))\,dG(y_F)\Big]$$

reservation earnings are set to equal the flow value of unemployment and the expected surplus associated with job offers. Note that for all values that R can take, the expected surplus from a full-time job exceeds the expected surplus from a part-time job.
Rearranging yields

$$R(\alpha,\gamma) = b + \beta\frac{\alpha}{1-\beta}\Bigg[\int_R^{\bar{y_F}}(y_F-R(\alpha,\gamma))\,dG(y_F) - \gamma\Bigg(\int_R^{\bar{y_F}}(y_F-R(\alpha,\gamma))\,dG(y_F) - \int_R^{\bar{y_P}}(y_P-R(\alpha,\gamma))\,dG(y_P)\Bigg)\Bigg]$$

Substituting $y_F = w$ and $y_P = \theta w$, and using the fact that $G(y_F) = F(w)$ and $w_{R,P} = \frac{R}{\theta}$, I rewrite the expression that implicitly defines reservation earnings as:

$$R(\alpha,\gamma) = b + \beta\frac{\alpha}{1-\beta}\Big[\int_R^{\bar{\bar{w}}}(w-R(\alpha,\gamma))\,dF(w) - \gamma\Big(\int_R^{\bar{w}}(w-R(\alpha,\gamma))\,dF(w) - \int_{\frac{R}{\theta}}^{\bar{\bar{w}}}(\theta w-R(\alpha,\gamma))\,dF(w)\Big)\Big] \tag{A.1}$$

Differentiating both sides of equation (A.1) with respect to α and applying the Leibniz

rule yields

$$\begin{aligned}\frac{\partial R(\alpha,\gamma)}{\partial \alpha} = \frac{\beta}{1-\beta}\Bigg[& \int_R^{\bar{\bar{w}}} (w - R(\alpha,\gamma))\, dF(w) \\ & - \gamma\Big(\int_R^{\bar{w}} (w - R(\alpha,\gamma))\, dF(w) - \int_{\frac{R}{\theta}}^{\bar{\bar{w}}} (\theta w - R(\alpha,\gamma))\, dF(w)\Big)\Bigg] \\ & + \frac{\beta\alpha}{1-\beta}\Big[- \frac{\partial R(\alpha,\gamma)}{\partial \alpha}(1 - F(R)) + \gamma \frac{\partial R(\alpha,\gamma)}{\partial \alpha}(1 - F(R)) \\ & - \gamma \frac{\partial R(\alpha,\gamma)}{\partial \alpha}\left(1 - F\left(\frac{R}{\theta}\right)\right)\Big]\end{aligned}$$

Rearranging, I get to the following expression

$$\frac{\partial R(\alpha,\gamma)}{\partial \gamma} = \frac{\frac{\beta}{1-\beta}\Bigg[\int_R^{\bar{\bar{w}}} (w - R(\alpha,\gamma))\, dF(w) - \gamma\Big(\int_R^{\bar{w}} (w - R(\alpha,\gamma))\, dF(w) - \int_{\frac{R}{\theta}}^{\bar{\bar{w}}} (\theta w - R(\alpha,\gamma))\, dF(w)\Big)\Bigg]}{1 + \frac{\beta\alpha}{1-\beta}\Big[(1 - F(R))(1-\gamma) + \gamma\left(1 - F\left(\frac{R}{\theta}\right)\right)\Big]}$$

Both the numerator and the denominator of the right-hand side are positive. Hence, $\frac{\partial R(\alpha,\gamma)}{\partial \gamma} > 0$, i.e. reservation earnings are increasing the perceived probability of receiving a job offer. □

Proof of Proposition 2

Proof. Differentiating both sides of equation (A.1) with respect to γ and applying the Leibniz rule yields

$$\begin{aligned}\frac{\partial R(\alpha,\gamma)}{\partial \gamma} = \frac{\beta\alpha}{1-\beta}\Bigg[& - (1 - F(R))\frac{\partial R(\alpha,\gamma)}{\partial \gamma} - \Big(\int_R^{\bar{w}} (w - R(\alpha,\gamma))\, dF(w) - \int_{\frac{R}{\theta}}^{\bar{\bar{w}}} (\theta w - R(\alpha,\gamma))\, dF(w)\Big) \\ & - \gamma\Big(- \frac{\partial R(\alpha,\gamma)}{\partial \gamma}(1 - F(R)) + \frac{\partial R(\alpha,\gamma)}{\partial \gamma}(1 - F(\frac{R}{\theta}))\Big)\Bigg]\end{aligned}$$

which yields the following expression

$$\frac{\partial R(\alpha,\gamma)}{\partial \gamma} = - \frac{\Big(\int_R^{\bar{w}} (w - R(\alpha,\gamma))\, dF(w) - \int_{\frac{R}{\theta}}^{\bar{\bar{w}}} (\theta w - R(\alpha,\gamma))\, dF(w)\Big)}{\Big[1 + \frac{\beta\alpha}{1-\beta}\Big((1 - F(R))(1-\gamma) + \gamma(1 - F(\frac{R}{\theta}))\Big)\Big]}$$

Because the expected surplus from a full-time always exceeds that of a part-time job, the numerator is positive. The denominator is also positive. It follows that $\frac{\partial R(\alpha,\gamma)}{\partial \gamma} < 0$, i.e. reservation earnings are decreasing in a workers' beliefs of receiving a part-time relative to a full-time job offer. □

Job finding probabilities

. The individual job-finding probability is defined as:

$$\lambda_i = \alpha^* \Big[\gamma^* P\Big(y_P \geq R_i(\alpha_i, \gamma_i) \Big) + (1-\gamma^*) P\Big(y_F \geq R_i(\alpha_i, \gamma_i) \Big) \Big] \tag{2}$$

that I rewrite as

$$\lambda_i = \alpha^* \Big[\gamma^* \Big(1 - F\Big(\frac{R_i(\alpha_i, \gamma_i)}{\theta} \Big) \Big) + (1-\gamma^*) \Big(1 - F(R_i(\alpha_i, \gamma_i)) \Big) \Big] \tag{3}$$

where λ_i represents the per-period probability of exiting unemployment. This probability depends on the true arrival rates of job offers, α^* and γ^*, as well as on women's beliefs about these parameters through their reservation earnings, $R_i(\alpha_i, \gamma_i)$, which are indexed by i to reflect heterogeneity in workers' beliefs. A second implication of equation (12) in the model is that $\lambda_L > \lambda_H$ at any point in time, implying that women from low-FLFP areas have higher job-finding rates due to behavioral differences driven by their beliefs. Specifically, since women with more pessimistic beliefs are less selective and have lower reservation earnings, they are less likely to reject job offers and more likely to exit unemployment earlier. It is important to note that this result relies on a simplifying assumption of the model—that job search effort is exogenously determined. An extended version of the model, presented in the online appendix, relaxes this assumption by allowing for endogenous search effort. This extension can reconcile the model with the empirical finding that the timing of job acceptance does not differ systematically between the two groups, despite differences in beliefs.

B Sample Description and Geographical Indicators

Table 1: Summary Statistics of Demographics, Performance and Family Background

	Female			Male			
	Mean	SD	Obs	Mean	SD	Obs	P-value
Individual characteristics							
Age at enrollment	24.3	4.0	182,792	24.5	4.1	133,678	0.00
GPA during Master	27.8	1.5	182,792	27.4	1.7	133,678	0.00
Final grade during Master	108.6	5.6	182,792	107.4	6.3	133,678	0.00
Time to completion of Master (years)	2.5	0.6	182,792	2.6	0.6	133,678	0.00
Bachelor grade	101.3	7.4	162,091	99.1	8.2	116,258	0.00
High school: academic track (%)	84.2	36.5	182,477	71.4	45.2	133,378	0.00
science (%)	40.3	49.0	182,477	56.7	49.5	133,378	0.00
humanities (%)	21.2	40.9	182,477	10.4	30.6	133,378	0.00
foreign language (%)	10.5	30.7	182,477	1.9	13.8	133,378	0.00
social sciences (%)	10.3	30.4	182,477	1.4	11.6	133,378	0.00
arts (%)	1.9	13.7	182,477	1.0	9.8	133,378	0.00
High school: technical track (%)	12.9	33.5	182,477	25.1	43.3	133,378	0.00
High school: vocational track (%)	1.2	10.9	182,477	1.7	12.9	133,378	0.00
International high-school (%)	1.7	12.9	182,477	1.8	13.3	133,378	0.02
High school grade	83.6	11.6	178,593	80.8	12.1	130,134	0.00
Field of study							
Science, chemistry, biology (%)	13.3	34.0	182,792	13.1	33.7	133,678	0.06
Engineering (%)	8.2	27.5	182,792	27.0	44.4	133,678	0.00
Humanities (%)	24.7	43.1	182,792	10.4	30.5	133,678	0.00
Political and social sciences (%)	11.6	32.0	182,792	7.9	26.9	133,678	0.00
Economics and statistics (%)	18.5	38.9	182,792	24.3	42.9	133,678	0.00
Psychology (%)	11.7	32.1	182,792	3.1	17.4	133,678	0.00
Healthcare (%)	4.0	19.7	182,792	2.1	14.4	133,678	0.00
Architecture (%)	3.9	19.5	182,792	4.9	21.6	133,678	0.00
Agriculture (%)	1.9	13.8	182,792	2.9	16.9	133,678	0.00
Family background							
Matched to administrative records	91.7	27.6	182,792	89.6	30.6	133,678	0.00
Mother: university education (%)	18.9	39.2	167,637	22.0	41.4	119,745	0.00
Father: university education (%)	20.0	40.0	167,637	24.0	42.7	119,745	0.00
Mother: high-school education (%)	50.3	50.0	167,637	50.9	50.0	119,745	0.00
Father: high-school education (%)	46.0	49.8	167,637	47.2	49.9	119,745	0.00
Mother is in labor force (%)	71.0	45.4	163,753	73.2	44.3	116,921	0.00
Father is in labor force (%)	99.3	8.0	162,735	99.4	7.5	117,051	0.00
Mother: low SES (%)	59.5	49.1	163,753	55.8	49.7	116,921	0.00
Mother: medium SES (%)	30.2	45.9	163,753	32.6	46.9	116,921	0.00
Mother: high SES (%)	10.4	30.5	163,753	11.6	32.0	116,921	0.00
Father: low SES (%)	45.6	49.8	162,735	40.5	49.1	117,051	0.00
Father: medium SES (%)	23.1	42.1	162,735	24.2	42.8	117,051	0.00
Father: high SES (%)	31.3	46.4	162,735	35.3	47.8	117,051	0.00

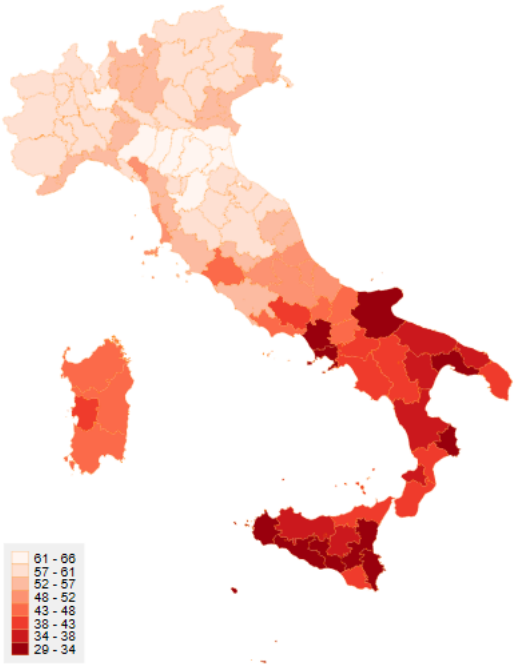
Notes. The table compares mean characteristics between female and male students in the sample. Variables in this panel were collected from administrative data and the institutional survey (available for 91% of students). Changes in the number of observations across variables reflect the unavailability of information for a subset of students who either denied consent to share their data with researchers or did not respond to specific survey questions. Socioeconomic status (SES) is categorized based on parents' occupations into 12 classes.

Table 2: Summary Statistics of Labor Market Outcomes and Job-Search Process

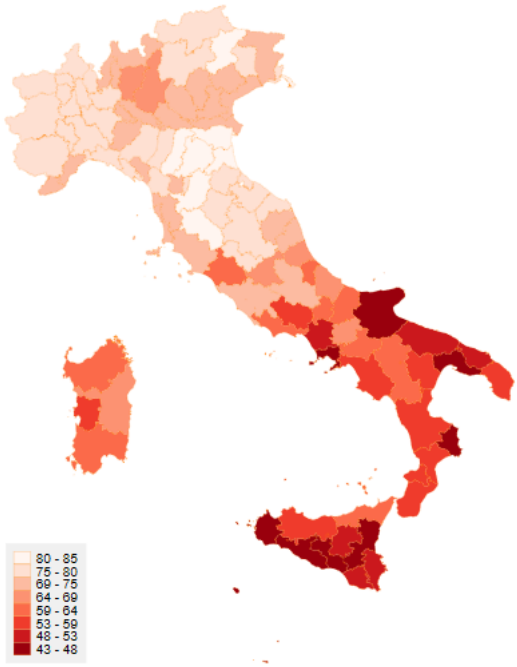
	Female			Male			
	Mean	SD	Obs	Mean	SD	Obs	P-value
Respond to survey (%)	73.7	44.0	182,792	73.2	44.3	133,678	0.00
Married/cohabiting (%)	16.1	36.8	134,506	9.5	29.3	97,709	0.00
Has children (%)	3.7	18.8	134,514	2.2	14.6	97,724	0.00
Currently employed (%)	53.9	49.8	134,681	61.8	48.6	97,823	0.00
Not currently employed, but has been (%)	15.1	35.8	134,681	11.2	31.6	97,823	0.00
Never employed (%)	31.0	46.3	134,681	27.0	44.4	97,823	0.00
Not currently employed:							
Further education (%)	12.1	32.6	134,479	12.5	33.1	97,663	0.00
Internship/training (%)	12.7	33.3	134,479	9.5	29.3	97,663	0.00
Unemployed searching for a job (%)	16.0	36.7	134,674	12.1	32.7	97,818	0.00
Out of labor force (%)	5.2	22.3	134,674	4.0	19.7	97,818	0.00
Currently employed:							
Net monthly earnings (€)	1,077.8	499.3	69,659	1,324.5	509.6	57,494	0.00
Weekly hours worked	32.9	13.2	69,659	38.6	10.9	57,494	0.00
Full-time job (%)	69.3	46.1	69,659	86.2	34.5	57,494	0.00
Hourly wage	8.9	6.4	69,659	8.9	5.7	57,494	0.67
High earnings occupation (%)	36.7	48.2	68,231	61.5	48.7	56,680	0.00
High full-time occupation (%)	51.3	50.0	68,231	74.5	43.6	56,680	0.00
High earnings industry (%)	34.3	47.5	68,434	48.2	50.0	56,835	0.00
High full-time industry (%)	38.1	48.6	68,434	62.0	48.5	56,835	0.00
Permanent contract (%)	23.0	42.1	69,431	29.4	45.6	57,342	0.00
Fixed-term contract (%)	54.2	49.8	69,431	52.2	50.0	57,342	0.00
Self-employment (%)	16.1	36.8	69,431	15.4	36.1	57,342	0.04
No contract (%)	6.7	25.0	69,431	3.0	17.1	57,342	0.00
Private sector (%)	76.7	42.3	69,570	86.1	34.6	57,450	0.00
Public sector (%)	16.5	37.1	69,570	11.1	31.4	57,450	0.00
No profit (%)	6.9	25.3	69,570	2.8	16.5	57,450	0.00
Use skills acquired during Master (%)	41.8	49.3	69,598	47.3	49.9	57,457	0.00
Job satisfaction (0-10)	7.2	2.0	69,580	7.4	1.7	57,453	0.00
Job-search process							
Job search: months from grad.	0.7	1.8	68,654	0.6	1.5	56,382	0.00
Accept offer: months from grad.	3.0	3.5	69,380	2.7	3.3	57,356	0.00
Number of jobs from grad.	1.3	0.6	69,594	1.2	0.6	57,454	0.00
Current job: first job after grad. (%)	80.3	39.8	69,594	81.0	39.2	57,454	0.00
On-the-job search | part-time (%)	58.0	49.4	21,390	55.9	49.7	7,918	0.00
On-the-job search | full-time (%)	30.8	46.2	48,262	28.8	45.3	49,573	0.00
Received job offer | part-time (%)	19.1	39.3	21,392	19.4	39.5	7,918	0.00
Received job offer | full-time (%)	21.5	41.1	48,267	26.5	44.1	49,576	0.00
Received job offer | unemployed (%)	19.3	39.5	21,589	22.1	41.5	11,870	0.00
Number of job-search channels	3.4	1.8	70,887	3.5	1.9	49,709	0.00
Prefer full-time to part-time job (%)	93.6	24.5	165,921	96.1	19.4	118,499	0.00
Available to accept part-time job (%)	82.4	38.1	163,200	61.6	48.6	116,434	0.00

Notes. The table compares mean characteristics between female and male students in the sample. Variables in this panel were collected through the follow-up survey conducted one year after graduation, completed by approximately 73% of students. Information on earnings, hours worked, and other job characteristics is only collected for individuals with an employment relationship (including those working in the informal sector), but is not available for individuals in internships or occupation-specific training programs (*praticantato*). Data on preference for full-time versus part-time jobs comes from responses to the pre-graduation survey, completed by 91% of students.

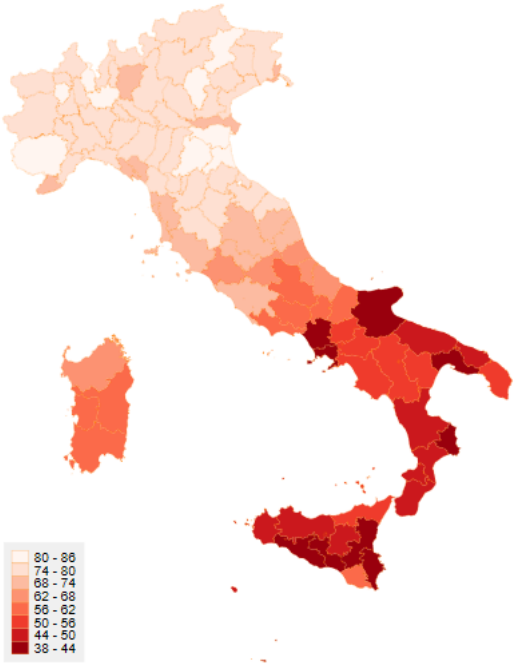
Figure 1: Heatmaps of various geographical indicators of gender equality



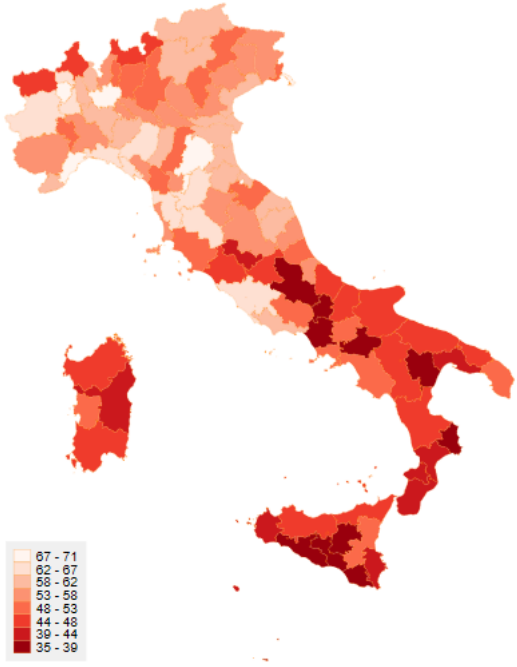
(a) FLFP (%) - Age: 15-64



(b) FLFP/MLFP (%) - Age: 15-64



(c) FLFP (%) - Age: 25-34



(d) % of firms without preference for male workers

Notes. These figures depict the geographical distribution of various gender equality indicators across Italian provinces. Panels (a) and (b) present the FLFP and the ratio FLFP/MLFP for all women aged 15–64. Panel (c) shows the FLFP for young women aged 25–34 in Italy. All these indicators are calculated as averages over the period 2004–2007. Panel (d) displays the percentage of firms without hiring preferences for male workers in 2003.

Table 3: Summary statistics of geographical indicators of gender equality in the sample, by student gender

	Female		**Male**		
	Mean	SD	Mean	SD	P-value
Female labor force participation (age: 15-64)	49.3	11.2	50.2	11.1	0.00
Female/Male labor force participation (age: 15-64)	66.3	11.9	67.2	11.8	0.00
Female labor force participation (age: 25-34)	64.6	15.3	65.8	15.1	0.00
Female/Male labor force participation (age: 25-34)	73.9	13.1	74.9	12.9	0.00
Male labor force participation (age: 15-64)	73.7	4.6	74.0	4.5	0.00
Male labor force participation (age: 25-34)	86.5	6.5	87.0	6.4	0.00
% of female graduates in full-time job	56.0	9.6	56.8	9.5	0.00
% of female/male graduates in full-time job	71.6	6.7	72.1	6.6	0.00
% of firms without hiring pref. for male workers	34.5	7.8	35.1	7.8	0.00
Historical literacy rates of female/male	81.3	13.2	82.2	12.9	0.00

Notes. The table presents summary statistics of the geographical indicators of gender equality (1–6) discussed in Section 3, broken down by students' gender. The sample includes 182,792 female and 133,678 male students. Students are assigned to provinces based on their province of residence prior to enrollment in the Master's program. The similarity in these statistics across genders indicates that, on average, students' geographical origins do not differ by gender.

Table 4: Summary statistics of other geographical indicators in the sample

Variable	Mean	SD	Min	Max	Obs
% of firms in service sector	75.2	5.2	58.7	83.3	316470
% of women with high-school educ	58.4	6.7	46.8	71.4	316470
Fertility rate	39.6	3.8	29.6	47.4	316470
Per capita income (municipality)	19062.4	4146.8	7330.5	46566.6	316470
Number of taxpayers (municipality)	193214.4	465215.8	29.0	1869353.0	316470
Childcare availability	18.5	5.1	7.0	33.0	316470

Notes. The table presents summary statistics of additional (non gender-specific) geographical characteristics in the sample. The unit of observation is the student. Students are assigned to provinces or municipalities based on their residence prior to enrollment in the Master's program. All measures are defined at the province level unless otherwise specified.

Table 5: Pairwise correlations between FLFP rates and other geographical indicators

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) FLFP	1.000										
(2) FLFP/MFLP	0.989	1.000									
(3) MLFP	0.905	0.836	1.000								
(4) Firm's culture	0.723	0.711	0.654	1.000							
(5) % of firms in service sector	-0.426	-0.381	-0.499	0.071	1.000						
(6) % of women (19-34) with high-school diploma	0.645	0.694	0.445	0.581	0.120	1.000					
(7) Fertility rate	-0.291	-0.355	-0.118	-0.008	0.203	-0.452	1.000				
(8) Per capita income	0.795	0.764	0.761	0.798	-0.213	0.410	0.036	1.000			
(9) SD of per capita income	0.167	0.174	0.108	0.372	0.199	0.131	0.133	0.426	1.000		
(10) Historical literacy rates of female vs. male	0.508	0.448	0.591	0.589	-0.173	-0.041	0.266	0.793	0.368	1.000	
(11) Childcare availability	0.662	0.662	0.554	0.642	0.017	0.645	-0.176	0.574	0.119	0.282	1.000

Notes. The table reports pairwise correlations between female labor force participation measures and other geographical indicators in the sample. The unit of observation is a student. Students are assigned to provinces based on their residence prior to enrollment in the Master. All measures are defined at the province level.

Table 6: Geographic mobility to universities in the sample, by students' gender

	Female		Male		
	Mean	SD	Mean	SD	P-value
Moved to another province for Master (%)	58.9	49.2	55.4	49.7	0.00
Moved to another region for Master (%)	31.3	46.4	29.1	45.4	0.00
Bachelor and Master in same univ. (%)	71.5	45.1	75.7	42.9	0.00
Indicators of gender equality in the province of study					
Female labor force participation (age: 15-64)	52.9	10.5	53.7	10.2	0.00
Female/Male labor force participation (age: 15-64)	70.2	11.3	71.0	11.0	0.00
Female labor force participation (age: 25-34)	69.1	14.2	70.2	13.7	0.00
Female/Male labor force participation (age: 25-34)	78.2	11.9	79.0	11.5	0.00
Male labor force participation (age: 15-64)	74.9	4.0	75.1	3.8	0.00
Male labor force participation (age: 25-34)	87.7	6.1	88.2	5.9	0.00
% of female graduates in full-time	58.8	8.8	59.7	8.6	0.00
% of female/male graduates in full-time	73.3	6.0	73.9	5.8	0.00
% of firms without hiring pref. for male workers	58.5	8.2	59.1	7.8	0.00

Notes. The table presents summary statistics on students' mobility for graduate studies. In addition to mobility rates by gender, it reports information on the province of study, specifically local indicators of gender equality. As this information is drawn from administrative records, it is available for all students in the sample—182,792 female and 133,678 male students. Women are, on average, slightly more mobile than men (upper panel), and their destinations are broadly comparable in terms of gender equality in the province of study.

Table 7: Geographic Mobility to Labor Markets in the Sample, by Students' Gender

	Female			Male			
	Mean	SD	Obs	Mean	SD	Obs	P-value
Work in province of studies (%)	45.1	49.8	69548	43.8	49.6	57417	0.0
Work in region of studies (%)	68.4	46.5	69548	65.3	47.6	57417	0.0
Work abroad (%)	5.0	21.7	69548	5.3	22.3	57417	0.0
Work outside province of origin (%)	44.1	49.7	69548	51.6	50.0	57417	0.0
Gender culture in province of work (excl. abroad)							
Female labor force participation (age 15-64)	54.6	9.7	66102	55.7	9.2	54400	0.0
Female/Male labor force participation (age 15-64)	71.8	10.4	66102	72.9	9.8	54400	0.0
Female labor force participation (age 25-34)	71.8	13.1	66102	73.1	12.2	54400	0.0
Female/Male labor force participation (age 25-34)	79.8	11.0	66102	80.9	10.2	54400	0.0
Male labor force participation (age 15-64)	75.7	3.8	66102	76.0	3.6	54400	0.0
Male labor force participation (age 25-34)	89.3	5.7	66102	89.8	5.4	54400	0.0
% of female graduates in full-time	60.7	8.5	66102	61.7	8.1	54400	0.0
% of female/male graduates in full-time	74.6	5.9	66102	75.3	5.6	54400	0.0
% of firms without hiring preference for male workers	58.5	8.3	66102	59.3	8.0	54400	0.0

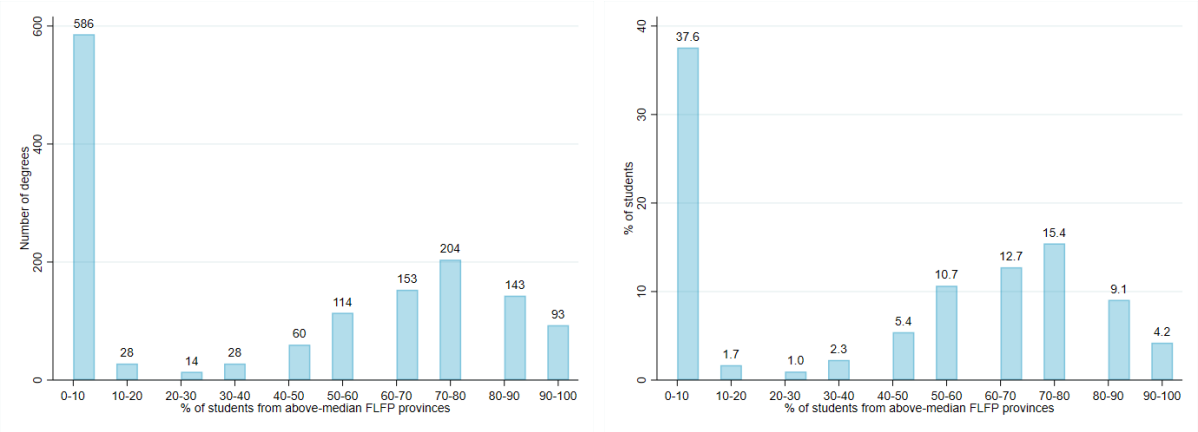
Notes. The table presents summary statistics on students' mobility to local labor markets one year after graduation. In addition to mobility rates by gender, it includes information on the characteristics of the province where students are employed. The sample consists of 69,659 female and 57,494 male students who are employed (excluding internships and training programs) at the time of the follow-up survey one year after graduation. The smaller sample size reflects missing data on the province of work for a small subset of individuals.

Table 8: Mobility patterns by FLFP in province of origin (Female sample)

	Q1 FLFP (N=48,896)		**Q4 FLFP** (N=44,103)		
	Mean	SD	Mean	SD	P-value
(1) Moved to another province for Master (%)	57.8	49.4	63.0	48.3	0.00
(2) Moved to another region for Master (%)	37.2	48.3	27.1	44.5	0.00
(3) Work in different province than birth (%)	54.8	49.8	37.8	48.5	0.00
Types of mobility (only for (1))					
FLFP (age: 15-64) in prov. of university	49.7	11.7	60.0	4.4	0.00
Size of university	33797.4	16373.0	36606.5	18288.8	0.00
Nb. of students in the degree	80.3	61.8	80.9	59.4	0.21
% of female students in the degree	69.0	18.6	65.6	18.5	0.00
% of movers in the degree	60.4	20.6	72.0	14.8	0.00
% of movers (region) in the degree	32.6	25.7	41.9	19.4	0.00
% of peers from above-median FLFP prov	27.0	31.3	67.1	17.4	0.00
Field of study (only for (1))					
Science, chemistry, biology (%)	13.8	34.5	12.6	33.2	0.00
Engineering (%)	8.3	27.5	6.2	24.2	0.00
Humanities (%)	25.7	43.7	27.1	44.5	0.00
Political and social sciences (%)	11.7	32.2	11.9	32.4	0.45
Economics and statistics (%)	14.2	34.9	17.0	37.6	0.00
Psychology (%)	15.6	36.3	12.3	32.9	0.00
Healthcare (%)	4.3	20.2	3.8	19.1	0.00
Architecture (%)	2.7	16.1	4.8	21.5	0.00
Agriculture (%)	1.4	11.8	2.2	14.6	0.00
Mobility to local labor markets (only for (1))					
FLFP in prov of work	48.5	13.3	61.0	3.5	0.00
Prov. of work = univ. (%)	29.7	45.7	20.0	40.0	0.00
Region of work = univ. (%)	52.4	49.9	63.5	48.1	0.00
Work abroad (%)	5.4	22.7	6.0	23.7	0.10
Work in different prov. than birth (%)	68.8	46.3	45.9	49.8	0.00

Notes. The table presents summary statistics on geographic mobility among female students, comparing those born in provinces in the first versus fourth quartile of FLFP. In addition to mobility rates, the table reports characteristics of mobility for the subsample of movers, who represent 57.8% and 63% of students from the first and fourth quartiles, respectively.

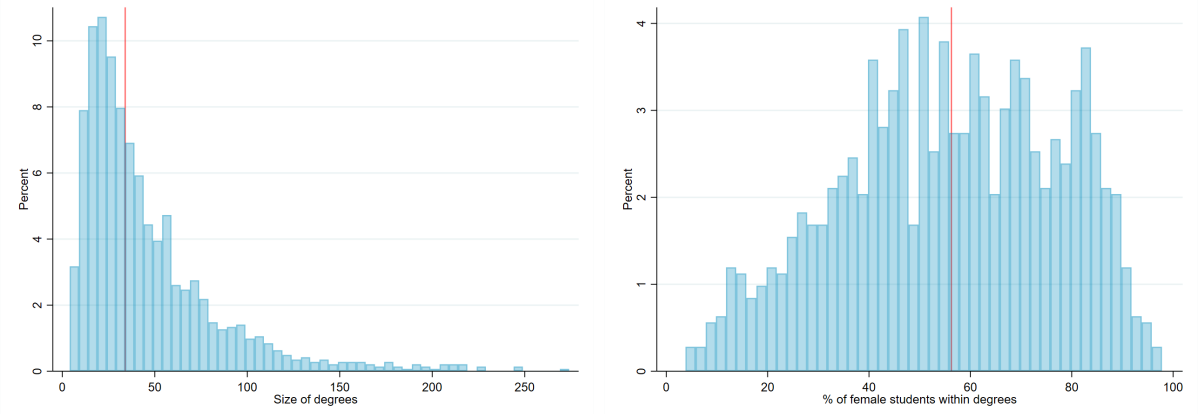
Figure 2: Distribution of students from above-median FLFP provinces across degrees



(a) Distribution of degrees **(b)** Students represented

Notes. These two graphs depict the distribution of students born in provinces with above-median FLFP across degree programs. Panel (A) shows the number of degrees (N = 1,572) falling into brackets based on the percentage of students from above-median FLFP areas in 2016: 0-10, ..., 90-100. One unit corresponds to a degree (N=1,572). Panel (B) displays the share of total students represented by degrees within each bracket. The distribution appears bimodal: 586 degree programs—enrolling approximately 37% of students—have between 0% and 10% of their students from above-median FLFP provinces. Among the remaining programs, the distribution is closer to normal, peaking in the 70–80% bracket.

Figure 3: Size of Master's programs and gender composition



(a) Size **(b)** Percentage of female students

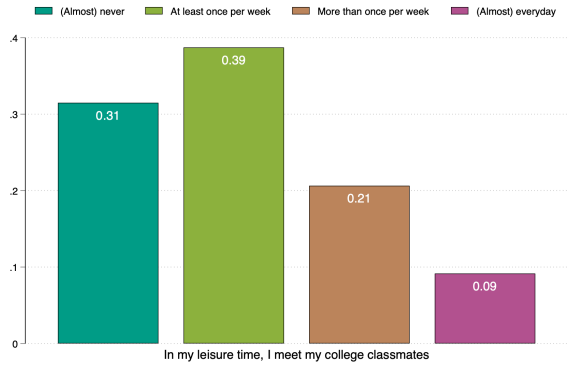
Notes. Panel (A) shows the distribution of degrees by their size (i.e., number of enrolled students). Panel (B) displays the distribution of degrees by the percentage of female students. In both panels, each unit represents a single degree program (N = 1,572). Red vertical lines indicate the median of each distribution. Data refer to the year 2016.

Table 9: Characteristics of Master's Programs

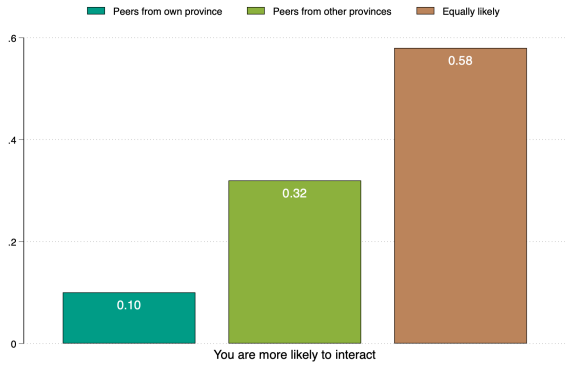
	Mean	SD	p50	Min	Max
Size of degree	48.0	43.9	35.0	4.0	410.0
% of female students	55.6	21.3	56.3	3.8	97.1
% of movers	55.3	23.2	56.3	0.0	100.0
% of movers (region)	28.5	23.1	25.0	0.0	91.7
% of students from above-median FLFP provs.	40.8	36.3	50.0	0.0	100.0
% of international students	2.3	6.0	0.0	0.0	55.0
% of students with BSc at same univ.	72.1	22.9	77.8	0.0	100.0

Notes. The table presents summary statistics of the main degree characteristics, averaged across the years 2012–2016. The unit of observation is a degree, with 1,572 degrees included in the sample.

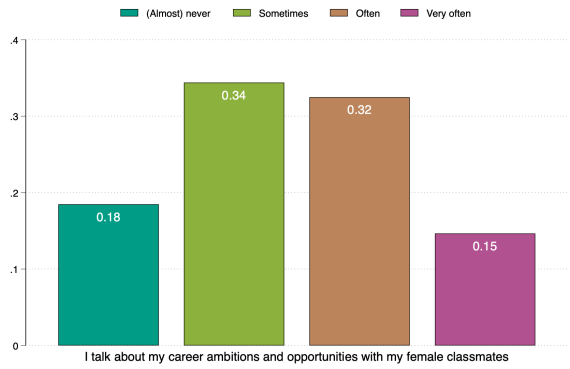
Figure 4: Quantity and quality of social interactions



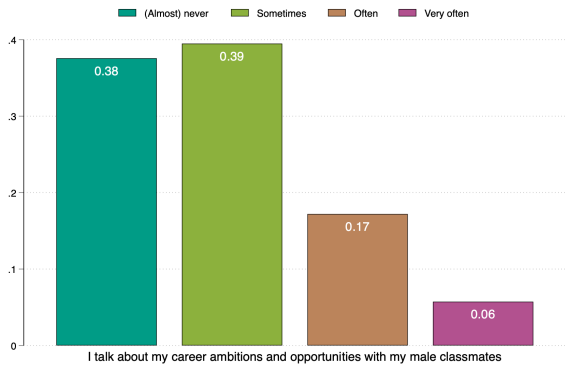
(a) Frequency



(b) Network structure



(c) Career opportunities



(d) Career opportunities

Notes. This figure shows responses from female students to a novel survey I conducted across various fields at the University of Bologna (N=490). Panels (A) and (B) combine responses from both first- and second-year students, as there are no meaningful differences in the network structure over time. Panels (C) and (D) display responses from students at the start of their second year (N=171), since students are significantly less likely to discuss career opportunities at the beginning of their first year. The questions asked are shown on the horizontal axes.

Table 10: Gender Differences in Labor Market Participation

	(1) Out of LF	(2) Has contract in LM	(3) Employed	(4) Internship
Female	-0.001	0.002	-0.012***	0.015***
	(0.001)	(0.002)	(0.003)	(0.001)
GPA	✓	✓	✓	✓
Degree FEs	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓
Observations	232,492	232,504	232,504	232,142
R-squared	0.023	0.117	0.128	0.080

Notes. The table reports coefficients from regressions of graduates' labor market participation on a female dummy, including degree and cohort fixed effects and controlling for GPA. Column 1: indicator for whether a student is out of the labor force. Column 2: indicator of whether a student is working at the time of the survey, regardless of contract type. Column 3: indicator for employment with a standard employment relationship (excluding internships and training programs) one year after graduation. Column 4: indicator for employment with an internship contract. Standard errors clustered at the degree level.

Table 11: The gender earnings gap at labor market entry, controlling for job types

	(1) Log(monthly earnings)	(2) Log(weekly hours)	(3) Pr(fulltime)	(4) Log(wage)
Female	-0.087***	-0.057***	-0.032***	-0.030***
	(0.003)	(0.003)	(0.002)	(0.003)
GPA	✓	✓	✓	✓
Job characteristics	✓	✓	✓	✓
Degree FEs	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓
Observations	127,153	127,153	127,153	127,153
R-squared	0.407	0.382	0.381	0.181

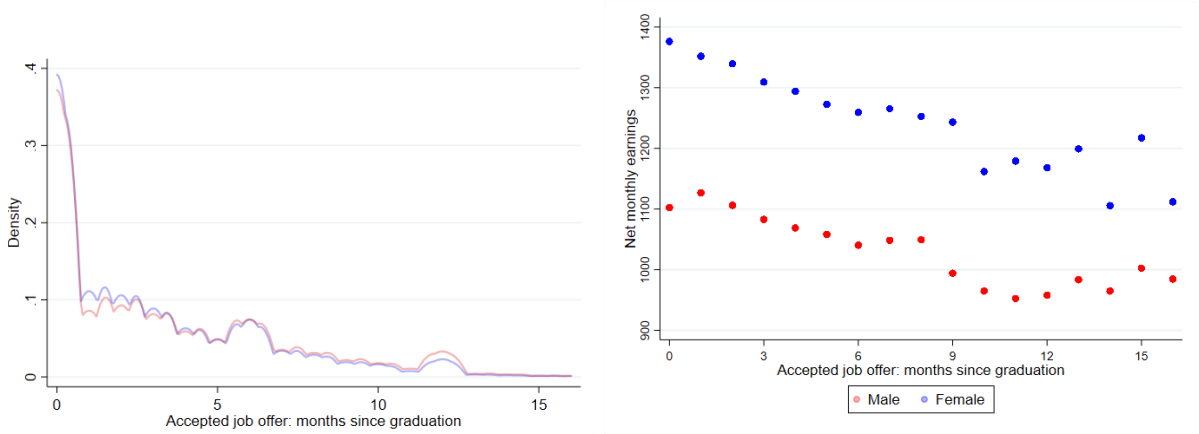
Notes. The table reports coefficients from regressions of graduates' labor market outcomes on a female dummy, after including degree and cohort fixed effects and controlling for covariates (GPA, province of work FEs, occupation FEs (20 classes), industry FEs (21 classes)). The sample consists of female and male students who are employed one year post graduation. Standard errors are clustered at the degree level.

Table 12: The gender earnings gap excluding individuals with children or married

	(1) Log(monthly earnings)	(2) Log(weekly hours)	(3) Pr(fulltime)	(4) Log(wage)
Female	-0.107***	-0.080***	-0.046***	-0.027***
	(0.004)	(0.004)	(0.003)	(0.003)
GPA	✓	✓	✓	✓
Degree FEs	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓
Observations	106,360	106,360	106,360	106,360
Nb. of degrees	1,570	1,570	1,570	1,570
R-squared	0.314	0.269	0.309	0.093

Notes. The table reports coefficients from regressions of graduates' labor market outcomes on a female dummy, after including degree and cohort fixed effects and controlling for GPA. The sample consists of female and male students employed one year post graduation, excluding individuals with children or those who are married or cohabiting with a partner. Standard errors are clustered at the degree level.

Figure 5: Gender gaps and timing of job acceptances



(a) Timing of job acceptances **(b)** Evolution of gender earnings gap

Notes. In both Panels, men are in blue and women in red. Panel (A) displays the distribution of the timing of job acceptance, measured in months from the graduation date, in the samples of female and male graduates. A value of 0 corresponds to jobs secured either prior to graduation or within the first month post-graduation. Panel (B) shows the average earnings of female and male workers by the month of job acceptance.

Table 13: Selection of female movers by FLFP in place of birth

	(1) Low FLFP	(2) High FLFP	(3) P-value	(4) Obs
Individual characteristics				
Age at enrollment	23.84	23.83	0.84	16,496
Bachelor grade	101.01	101.84	0.00	14,736
High-school grade	87.58	83.37	0.00	16,123
High school type: academic track (%)	88.78	81.38	0.00	16,463
science (%)	47.64	41.52	0.00	16,463
humanities (%)	23.70	15.16	0.00	16,463
foreign language (%)	9.12	13.15	0.00	16,463
social sciences (%)	7.19	9.66	0.00	16,463
arts (%)	1.13	1.89	0.00	16,463
High school type: technical track (%)	9.89	15.84	0.00	16,463
High school type: vocational track (%)	0.91	0.80	0.54	16,463
Family background				
Mother: university degree (%)	19.03	19.67	0.51	15,185
Father: university degree (%)	19.82	19.58	0.82	15,185
Mother: high-school degree (%)	50.42	52.72	0.03	15,185
Father: high-school degree (%)	47.26	46.25	0.37	15,185
Mother is in the LF (%)	62.24	81.84	0.00	14,866
Father is in the LF (%)	99.36	99.38	0.93	14,766
Mother: low SES (%)	61.15	55.87	0.00	14,866
Mother: medium SES (%)	30.46	32.34	0.08	14,866
Mother: high SES (%)	8.40	11.78	0.00	14,866
Father: low SES (%)	45.62	45.56	0.96	14,766
Father: medium SES (%)	26.22	20.97	0.00	14,766
Father: high SES (%)	28.16	33.47	0.00	14,766

Notes. This table examines selection—based on ability, educational histories, and socio-economic background—of female movers (individuals not working in their province of birth), categorized by FLFP quartiles (top vs. bottom). For each pre-determined characteristic, equation 1 is estimated. Columns (1) and (2) show predicted values for each group, and Column (3) reports the p-value testing the significance of α.

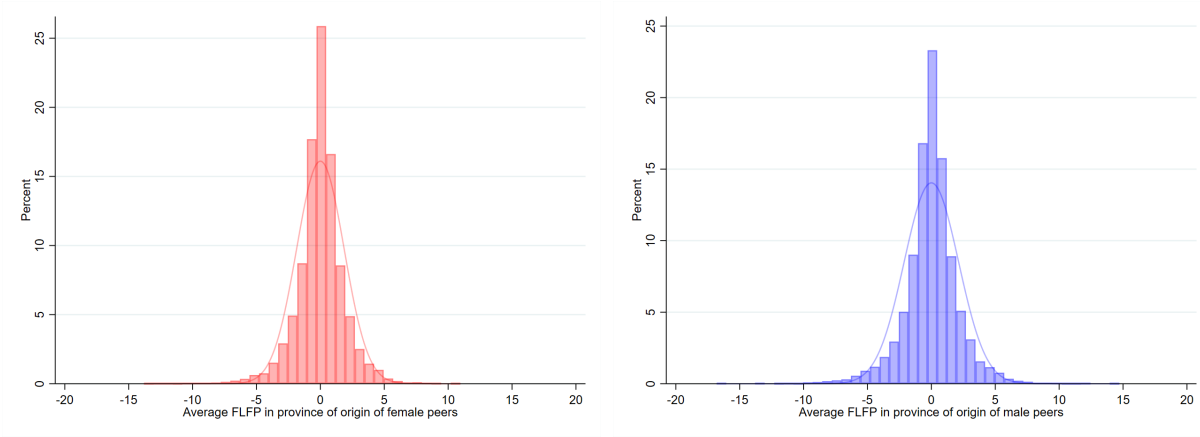
Table 14: Persistence of Labor Market Participation (Male Movers)

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(weekly hours)			Pr(fulltime)		
Q4 vs. Q1 FLFP	0.039***	0.039***	0.038***	0.011*	0.008	0.08
	(0.008)	(0.008)	(0.009)	(0.006)	(0.006)	(0.006)
Province of job FEs		✓	✓		✓	✓
GPA			✓			✓
Mother's occupation			✓			✓
Father's occupation			✓			✓
Degree FEs	✓	✓	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓	✓	✓
N	15,597	15,595	14,014	15,597	15,595	14,014

Notes. The table reports coefficients from separate regressions of men's labor market outcomes on a dummy variable indicating whether the student originates from a province with FLFP in the highest vs. lowest quartile. All regressions include controls for degree and cohort fixed effects. The sample consists of male movers, defined as men working in a different province from their birth province, who are employed one year post-graduation. Variations in sample sizes across columns arise from missing parental background data for some students. Standard errors are clustered at the degree level.

C Validity of the Empirical Strategy and Results

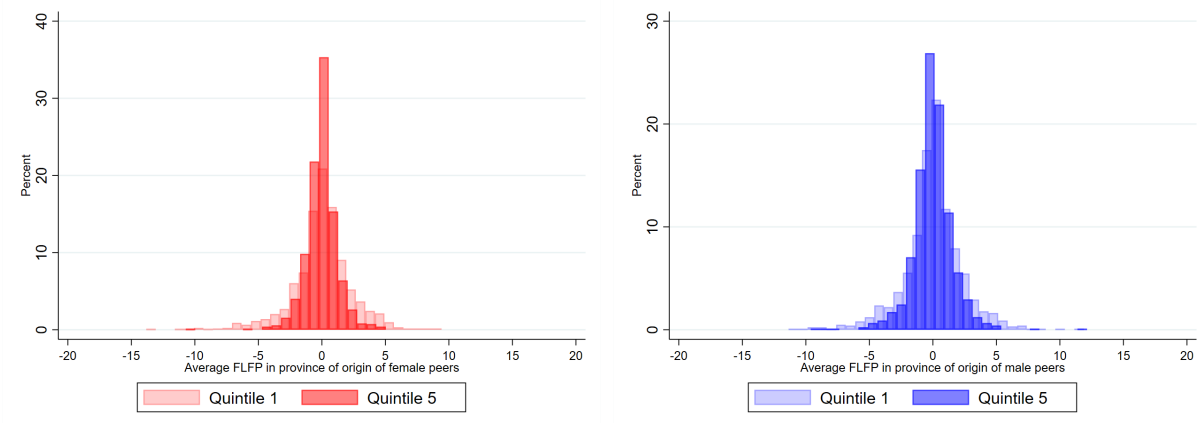
Figure 6: Year-to-Year Variation in Students' Geographical Origins within Programs



(a) Female peers (b) Male peers

Notes. The figure plots the distribution of residuals from a OLS regression of the average FLFP in the province of origin of female (Panel a) or male students (Panel b) on cohort and degree fixed effects. One observation corresponds to a degree-cohort pair. Histograms are presented by bins of 0.75. The normal distribution is plotted for comparison.

Figure 7: Year-to-Year Variation in Students' Geographical Origins by Program Size



(a) Female peers (b) Male peers

Notes. The figure plots the distribution of residuals from a OLS regression of the average FLFP in the province of origin of female (Panel a) or male students (Panel b) on cohort and degree fixed effects. The distributions are shown separately for degree programs in the first and highest quintiles of size. Degree programs are divided into quintiles based on their average size across five cohorts: the first quintile includes degrees with fewer than 22 students, while the fifth quintile includes degrees with 70 to 410 students. Each observation represents a degree-cohort pair. Histograms are presented by bins of 0.75.

Table 15: Balancing tests for cohort composition - Female students

Panel A. Educational history and ability

	(1) Age	(2) HS science	(3) HS humanities	(4) HS foreign languages	(5) HS social sciences	(6) HS vocational	(7) BSc grade	(8) BSc grade > p50
(Mean)	(24.3)	(0.40)	(0.21)	(0.11)	(0.10)	(0.01)	(101.3)	(0.50)
$\hat{\delta}^{FP}$	-0.030	-0.003	0.002	0.001	0.003	0.002	0.078	-0.001
	(0.092)	(0.006)	(0.005)	(0.004)	(0.004)	(0.001)	(0.124)	(0.008)
$\hat{\delta}^{MP}$	-0.110	-0.009*	-0.000	0.002	-0.004	0.001	-0.009	-0.001
	(0.095)	(0.005)	(0.004)	(0.003)	(0.004)	(0.001)	(0.090)	(0.006)
Degree FEs	✓	✓	✓	✓	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	182,792	182,792	182,792	182,792	182,792	182,792	162,091	162,091
R-squared	0.168	0.139	0.107	0.125	0.128	0.020	0.204	0.149

Panel B. Parental background

	(1) Mother: univ.	(2) Father: univ.	(3) Mother: HS	(4) Father: HS	(5) Mother: low SES	(6) Mother: high SES	(7) Father: low SES	(8) Father: high SES
(Mean)	(0.19)	(0.20)	(0.50)	(0.46)	(0.59)	(0.10)	(0.46)	(0.31)
$\hat{\delta}^{FP}$	-0.002	-0.009	0.007	-0.005	-0.009	-0.004	0.007	-0.007
	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.006)	(0.007)	(0.007)
$\hat{\delta}^{MP}$	-0.004	-0.006	-0.001	0.006	0.007	-0.002	0.008	0.001
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
Degree FEs	✓	✓	✓	✓	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	167,637	167,637	167,637	167,637	163,753	163,753	162,735	162,735
R-squared	0.043	0.042	0.019	0.015	0.039	0.026	0.036	0.038

Notes. The table reports OLS estimates of $\hat{\delta}^{FP}$ and $\hat{\delta}^{MP}$ from equation 2. Each column corresponds to a separate regression where the dependent variable is a pre-determined covariate: educational history and ability (Panel A) or parental background (Panel B). Regressions include cohort and degree fixed effects. Means are shown in parentheses. The sample includes all female students (N = 182,792). Sample sizes vary due to missing covariates from institutional surveys. Regressors are standardized; dependent variables are not. Standard errors clustered at the degree level.

Table 16: Balancing tests for cohort composition – Male students

Panel A. Educational history and ability

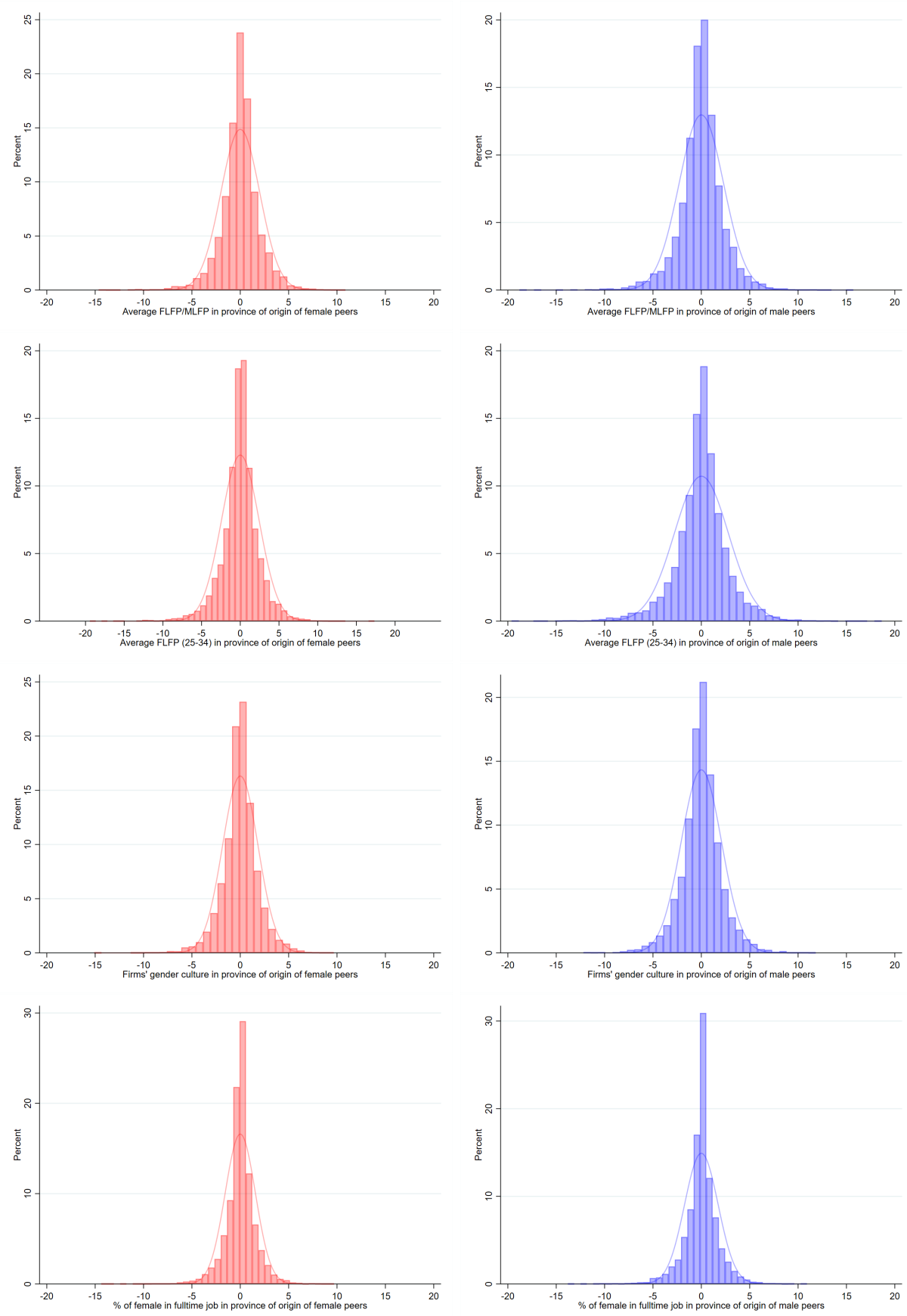
	(1) Age	(2) HS science	(3) HS humanities	(4) HS foreign languages	(5) HS social sciences	(6) HS vocational	(7) BSc grade	(8) BSc grade > p50
(Mean)	(24.5)	(0.57)	(0.10)	(0.02)	(0.01)	(0.02)	(99.1)	(0.50)
$\hat{\delta}^{FP}$	0.045	0.010	-0.006	0.000	-0.001	0.000	0.239*	0.017**
	(0.059)	(0.006)	(0.004)	(0.002)	(0.001)	(0.002)	(0.129)	(0.008)
$\hat{\delta}^{MP}$	-0.070	-0.003	0.004	-0.002	0.003	-0.000	-0.136	-0.005
	(0.074)	(0.007)	(0.005)	(0.002)	(0.002)	(0.002)	(0.124)	(0.008)
Degree FEs	✓	✓	✓	✓	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	133,678	133,678	133,678	133,678	133,678	133,678	116,258	116,258
R-squared	0.218	0.106	0.121	0.070	0.055	0.044	0.234	0.173

Panel B. Parental background

	(1) Mother: univ.	(2) Father: univ.	(3) Mother: HS	(4) Father: HS	(5) Mother: med SES	(6) Mother: high SES	(7) Father: med SES	(8) Father: high SES
(Mean)	(0.22)	(0.24)	(0.51)	(0.47)	(0.33)	(0.12)	(0.24)	(0.35)
$\hat{\delta}^{FP}$	-0.000	-0.012**	-0.012*	0.005	-0.001	-0.000	0.009	-0.007
	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.006)	(0.007)	(0.007)
$\hat{\delta}^{MP}$	-0.005	-0.001	0.000	0.004	-0.004	-0.004	-0.015**	0.014*
	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.006)	(0.007)	(0.007)
Degree FEs	✓	✓	✓	✓	✓	✓	✓	✓
Cohort FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	119,745	119,745	119,745	119,745	116,921	116,921	117,051	117,051
R-squared	0.037	0.036	0.020	0.019	0.038	0.030	0.033	0.041

Notes. The table reports OLS estimates of $\hat{\delta}^{FP}$ and $\hat{\delta}^{MP}$ from equation 2. Each column corresponds to a different regression, where the dependent variables are pre-determined covariates of a student, related to educational history and ability (Panel A), and parental background (Panel B). Regressions include cohort and degree fixed effects. Below each variable name, sample means are shown in parentheses. The sample consists of all male students in the sample (N=133,678). Variations in sample sizes across columns arise from missing information on some of the covariates. All regressors are standardised. Standard errors are clustered at the degree level.

Figure 8: Year-to-Year Variation in Students' Geographical Origins



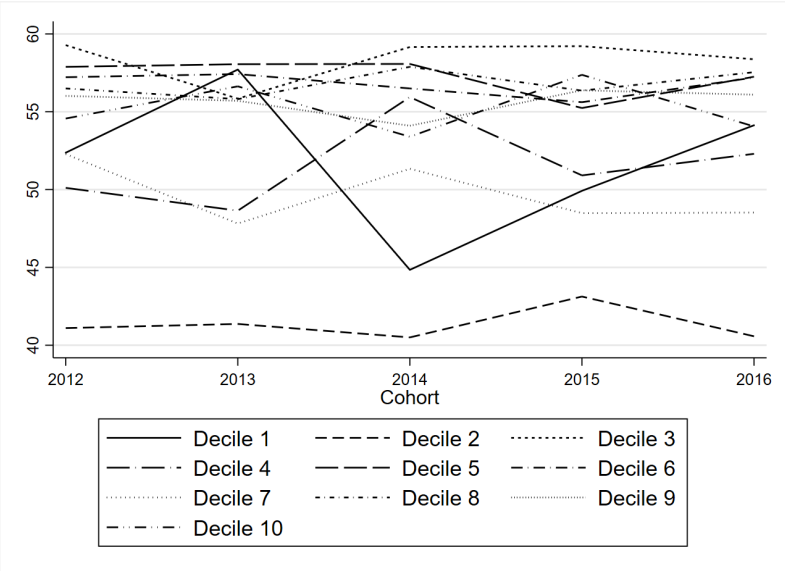
Notes. The figure displays the distribution of residuals from an OLS regression of the average characteristic in the province of origin for female (red) and male (blue) students on cohort and degree fixed effects. Each observation corresponds to a degree-cohort pair. Histograms are shown with bin widths of 0.75.

Table 17: Raw and Residual Variation of Additional Peers' Measures

	Mean	SD	Min	Max
A: Avg FLFP (25–34) in province of origin of female peers				
Raw cohort variable	65.00	11.93	39.85	85.00
Residuals: net of degree and cohort fixed effects	0.00	2.43	-19.43	16.92
B: Avg FLFP (25–34) in province of origin of male peers				
Raw cohort variable	65.09	12.02	39.33	85.00
Residuals: net of degree and cohort fixed effects	0.00	2.81	-24.04	18.37
C: Avg FLFP/MLFP in province of origin of female peers				
Raw cohort variable	66.76	8.88	43.62	85.36
Residuals: net of degree and cohort fixed effects	0.00	2.01	-14.64	10.59
D: Avg FLFP/MLFP in province of origin of male peers				
Raw cohort variable	66.81	8.99	43.02	85.29
Residuals: net of degree and cohort fixed effects	0.00	2.31	-18.80	15.40
E: % full-time female graduates in province of female peers				
Raw cohort variable	55.93	7.53	40.11	68.93
Residuals: net of degree and cohort fixed effects	0.00	1.56	-14.37	9.04
F: % full-time female graduates in province of male peers				
Raw cohort variable	55.95	7.59	40.11	68.93
Residuals: net of degree and cohort fixed effects	0.00	1.74	-13.79	10.48
G: Firms' gender culture in province of origin of female peers				
Raw cohort variable	53.88	5.88	37.00	71.00
Residuals: net of degree and cohort fixed effects	0.00	1.83	-15.09	9.31
H: Firms' gender culture in province of origin of male peers				
Raw cohort variable	54.09	6.04	36.00	68.00
Residuals: net of degree and cohort fixed effects	0.00	2.09	-12.18	11.08

Notes. The table reports descriptive statistics for the main measures of gender culture in the province of origin of female (Panel A) and male (Panel B) peers, before and after removing degree and cohort fixed effects. The unit of observation is a degree-cohort pair, leading to a total of 7,160 observations.

Figure 9: Time Series Evolution of Provincial FLFP Across Peers, by Deciles of Program's Size



Notes. This figure presents the time series evolution of the average FLFP in the province of origin of female peers within 10 randomly selected degree programs. Programs were first divided into deciles based on their average size across all years, and one program was randomly chosen from each decile.

Table 18: Raw and Residual Variation of Peers' Measures by Quintiles of Degree Size

	Mean	SD	Min	Max
A: Avg FLFP in province of origin of female peers				
Quintile 1 (<22 students)				
Raw cohort variable	48.68	8.87	32.09	66.18
Residuals: net of degree and cohort FEs	-0.00	2.37	-13.83	9.05
Quintile 2 (22–31 students)				
Raw cohort variable	50.79	7.80	31.14	66.18
Residuals: net of degree and cohort FEs	0.00	2.01	-9.68	8.21
Quintile 3 (32–42 students)				
Raw cohort variable	50.00	8.45	29.89	66.18
Residuals: net of degree and cohort FEs	0.00	1.91	-12.82	8.40
Quintile 4 (43–70 students)				
Raw cohort variable	49.73	8.38	31.02	65.99
Residuals: net of degree and cohort FEs	0.00	1.54	-9.77	10.78
Quintile 5 (70–413 students)				
Raw cohort variable	49.72	8.35	30.06	63.19
Residuals: net of degree and cohort FEs	0.00	1.23	-10.72	4.77
B: Avg FLFP in province of origin of male peers				
Quintile 1 (<21 students)				
Raw cohort variable	48.76	9.09	29.87	66.18
Residuals: net of degree and cohort FEs	-0.00	2.37	-11.36	11.33
Quintile 2 (21–31 students)				
Raw cohort variable	50.76	7.86	32.09	65.10
Residuals: net of degree and cohort FEs	0.00	2.24	-13.17	9.65
Quintile 3 (32–42 students)				
Raw cohort variable	50.18	8.54	29.49	65.33
Residuals: net of degree and cohort FEs	0.00	2.11	-11.47	9.11
Quintile 4 (43–70 students)				
Raw cohort variable	49.78	8.40	29.77	63.71
Residuals: net of degree and cohort FEs	0.00	1.91	-9.50	14.47
Quintile 5 (71–410 students)				
Raw cohort variable	49.85	8.36	29.48	66.37
Residuals: net of degree and cohort FEs	0.00	1.55	-9.61	11.76

Notes. The table reports descriptive statistics for the average FLFP in the province of origin for female (Panel A) and male (Panel B) peers. These statistics are shown by quintiles of degree size. Quintiles are based on the average number of students across five cohorts. Student counts are shown in parentheses.

Table 19: Estimates of Peer Effects on Female Earnings and Labor Supply – Alternative Specification

	(1) Log(monthly earnings)	(2) Log(weekly hours)	(3) Pr(full-time)	(4) Log(hourly wage)
$\hat{\delta}^{FP}$	0.037***	0.033***	0.018*	0.003
	(0.013)	(0.012)	(0.009)	(0.012)
$\hat{\delta}^{MP}$	-0.001	-0.000	-0.003	-0.002
	(0.010)	(0.009)	(0.007)	(0.010)
Province of origin FEs	✓	✓	✓	✓
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	69,645	69,645	69,645	69,645
R-squared	0.290	0.248	0.282	0.102

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Notes. Relative to the baseline specification, this table includes province-of-origin fixed effects instead of using FLFP measures. All regressions control for cohort and degree fixed effects. The sample includes women employed one year after graduation with non-missing values for the outcomes and regressors. All regressors are standardized. Standard errors are clustered at the degree level.

Table 20: Peer Effects on Survey Response and Probability of Entering the Labor Market

Panel A. Female Sample

	(1)	(2)	(3)	(4)
	Pr(Response)	Pr(Work in First Year)	Pr(Employed Now)	Pr(Missing Salary)
(Mean)	(0.74)	(0.69)	(0.54)	(0.04)
$\hat{\delta}^{FP}$	-0.005	-0.002	0.002	0.002
	(0.006)	(0.007)	(0.008)	(0.004)
$\hat{\delta}^{MP}$	-0.005	0.003	-0.010*	0.001
	(0.005)	(0.006)	(0.006)	(0.003)
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	182,792	134,680	134,680	72,584
R-squared	0.052	0.114	0.129	0.027

Panel B. Male Sample

	(1)	(2)	(3)	(4)
	Pr(Response)	Pr(Work in First Year)	Pr(Employed Now)	Pr(Missing Salary)
(Mean)	(0.73)	(0.73)	(0.62)	(0.05)
$\hat{\delta}^{FP}$	0.007	-0.006	0.003	-0.001
	(0.006)	(0.007)	(0.008)	(0.004)
$\hat{\delta}^{MP}$	-0.004	-0.005	-0.002	0.000
	(0.006)	(0.007)	(0.008)	(0.005)
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	133,678	97,823	97,823	60,440
R-squared	0.057	0.112	0.140	0.036

Notes. OLS estimates of equation 2 for women (Panel A) and men (Panel B). The dependent variables are: (1) follow-up survey response, (2) any employment during the first year post-graduation, (3) current employment at follow-up, and (4) missing salary data (among currently employed). Standard errors are clustered at the degree level. All regressors are standardized. Sample sizes decrease across columns due to conditioning on response and employment status.

Table 21: Estimates of Peer Effects on Job Characteristics – Female Sample

	(1) Permanent	(2) No Contract	(3) Self-Employed	(4) Public Sector	(5) Non-Profit
δ^{FP}	-0.002	-0.007	-0.003	0.001	0.007
	(0.010)	(0.005)	(0.008)	(0.010)	(0.005)
δ^{MP}	-0.008	-0.004	-0.012*	0.001	0.003
	(0.007)	(0.004)	(0.007)	(0.008)	(0.005)
Degree FE	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓
Observations	69,417	69,417	69,417	69,556	69,556
R-squared	0.137	0.098	0.144	0.203	0.153

Notes. OLS estimates of regressions of job contract type and sector (one year after graduation) on the average female labor force participation (FLFP) in the provinces of origin of female and male peers, as well as FLFP in the individual's own province. All dependent variables are binary indicators. The regressions are estimated on the sample of employed women with non-missing job characteristic data. Standard errors are clustered at the degree level. All regressors are standardized.

Table 22: Estimates of Peer Effects on Earnings and Labor Supply – Male Sample

	(1) Log(Monthly Earnings)	(2) Log(Weekly Hours)	(3) Pr(Full-Time)	(4) Log(Hourly Wage)
$\hat{\delta}^{FP}$	0.013	-0.000	-0.001	0.014*
	(0.008)	(0.008)	(0.006)	(0.008)
$\hat{\delta}^{MP}$	0.013	-0.005	0.004	0.018*
	(0.011)	(0.010)	(0.008)	(0.010)
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	57,476	57,476	57,476	57,476
R-squared	0.246	0.233	0.270	0.107

Notes. OLS estimates of the effects of peers' gender culture on men's earnings and labor supply one year after graduation. The main regressors are the average female labor force participation (FLFP) in the provinces of origin of female peers ($\hat{\delta}^{FP}$) and male peers ($\hat{\delta}^{MP}$), as well as the FLFP in the individual's own province. All regressions include degree and cohort fixed effects. The sample includes employed men with non-missing outcome data. Standard

Table 23: Sensitivity to Indicators of Gender Equality in Peers' Provinces - Estimates of Peer Effects on Female Earnings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: log(monthly earnings)							
	Measures of peers' gender culture							
	FLFP	FLFP (young)	FLFP/MLFP	FLFP/MLFP (young)	% of female grad. full-time	female/male grad. full-time	Firms' culture	F/M Literacy
$\hat{\pi}^{FP}$	0.037***	0.041***	0.035***	0.036***	0.040***	0.041***	0.016**	0.029***
	(0.013)	(0.014)	(0.012)	(0.013)	(0.012)	(0.011)	(0.008)	(0.011)
$\hat{\pi}^{MP}$	-0.000	0.003	0.000	0.002	0.010	0.009	0.004	0.013
	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.009)	(0.006)	(0.009)
Degree FE	✓	✓	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	69,645	69,645	69,645	69,645	69,645	69,645	69,645	69,645
R-squared	0.287	0.287	0.287	0.287	0.288	0.288	0.287	0.287

Notes. The table presents estimates from equation 3, using alternative indicators of gender equality in peers' provinces. The dependent variable is log(monthly earnings) across all columns. Each column refers to a separate regression, where I use the average of a different characteristic of peers' province of origin, as specified in the labels. Regressions include degree (master x university) and cohort fixed effects. The sample comprises women who are employed one year post graduation and with non-missing information on the dependent variable. Standard errors clustered at degree level. All regressors are standardised.

Table 24: Estimates of Peer Effects on Female Earnings – Controls for Degree Trends

	(1) Log(Monthly Earnings)	(2) Log(Weekly Hours)	(3) Pr(Full-Time)	(4) Log(Hourly Wage)
$\hat{\delta}^{FP}$	0.045***	0.039***	0.029***	0.007
	(0.014)	(0.014)	(0.010)	(0.014)
$\hat{\delta}^{MP}$	-0.002	-0.009	-0.005	0.006
	(0.011)	(0.011)	(0.008)	(0.011)
Degree FE	✓	✓	✓	✓
Degree Trends	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	69,645	69,645	69,645	69,645
R-squared	0.308	0.266	0.299	0.124

Notes. OLS estimates of specification 2, augmented to include degree-specific linear time trends. The sample includes employed women one year after graduation with non-missing values for each dependent variable. Standard errors are clustered at the degree level. All regressors are standardized.

Table 25: Estimates of Peer Effects on Female Earnings – Controls for Region Trends

	(1) Log(Monthly Earnings)	(2) Log(Weekly Hours)	(3) Pr(Full-Time)	(4) Log(Hourly Wage)
$\hat{\delta}^{FP}$	0.036***	0.030**	0.019**	0.005
	(0.013)	(0.012)	(0.009)	(0.012)
$\hat{\delta}^{MP}$	-0.001	-0.001	-0.002	-0.001
	(0.010)	(0.009)	(0.007)	(0.009)
Degree FE	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	69,645	69,645	69,645	69,645
R-squared	0.288	0.246	0.280	0.100

Notes. OLS estimates of specification 2, augmented to include region-of-study-specific linear time trends. The sample includes employed women one year after graduation with non-missing values for each dependent variable. Standard errors are clustered at the degree level. All regressors are standardized.

Table 26: Estimates of Peer Effects on Female Earnings – Excluding Degrees with Trends in Size

	(1) Log(Monthly Earnings)	(2) Log(Weekly Hours)	(3) Pr(Full-Time)	(4) Log(Hourly Wage)
$\hat{\delta}^{FP}$	0.052***	0.029*	0.030***	0.021
	(0.015)	(0.015)	(0.011)	(0.014)
$\hat{\delta}^{MP}$	0.003	0.000	-0.002	0.002
	(0.012)	(0.011)	(0.008)	(0.010)
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	47,246	47,246	47,246	47,246
R-squared	0.286	0.250	0.278	0.095

Notes. OLS estimates of the effects of peers' gender culture on women's earnings and labor supply, excluding degrees with trends in enrollment size. The sample includes women in those degrees who are employed one year after graduation and have non-missing dependent variables. All regressions include cohort and degree fixed effects. Standard errors are clustered at the degree level. All regressors are standardized.

Table 27: Estimates of Peer Effects on Female Earnings, Excluding Degrees with Large Shocks to Composition

	(1) Benchmark	(2) Δ size<=p75	(3) Δ size<=p50	(4) Δ avg grades<=p75	(5) Δ avg grades<=p25	(6) Δ sd grades<=p75	(7) Δ sd grades<=p25
$\hat{\delta}^{FP}$	0.037***	0.049***	0.053***	0.037**	0.041*	0.036**	0.054**
	(0.013)	(0.013)	(0.015)	(0.015)	(0.025)	(0.014)	(0.022)
$\hat{\delta}^{MP}$	-0.000	-0.002	-0.001	-0.003	-0.002	0.001	-0.004
	(0.010)	(0.011)	(0.013)	(0.011)	(0.014)	(0.012)	(0.014)
Degree FE	✓	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓	✓
Nb. of degrees	1,572	1,163	770	1,170	390	1,171	389
Observations	69,645	58,363	42,518	59,040	25,564	60,613	28,741
R-squared	0.287	0.294	0.309	0.280	0.251	0.278	0.284

Notes. The table reports estimates from equation 2. The dependent variable is log(monthly earnings) in all columns. Regressions include cohort and degree fixed effects. The Table analyzes the sensitivity of estimates across different subsamples of degrees. Column (1) and (2) are based on a sample of degrees with cross-cohort changes in size below the 75th and 50th percentiles (definitions in Subsection 7.1). Column (3) and (4) are based on a sample of degrees with cross-cohort changes in average students' ability below the 75th or 25th percentile. Column (5) and (6) are based on a sample of degrees with cross-cohort changes in the sd of students' ability below the 75th or 25th percentile. The estimates are done on the sample of women, studying in these degrees, who are employed one year after graduation and with non-missing information on the dependent variables. Standard errors clustered at degree level. All regressors are standardised.

Table 28: Sensitivity to Sample Restrictions - Estimates of Peer Effects on Female Earnings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Degree size					Students with Bsc in same uni	
	Benchmark	>p10	<=p90	<=mean	>mean	>p90	<=p90	<=p25
$\hat{\delta}^{FP}$	0.037***	0.032**	0.039***	0.050***	0.017	0.017	0.037***	0.048**
	(0.013)	(0.013)	(0.014)	(0.016)	(0.020)	(0.029)	(0.013)	(0.019)
$\hat{\delta}^{MP}$	-0.000	-0.000	-0.004	-0.014	0.015	0.011	0.000	0.008
	(0.010)	(0.010)	(0.012)	(0.012)	(0.016)	(0.017)	(0.010)	(0.013)
Degree FE	✓	✓	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓	✓	✓
Nb. of degrees	1,572	1,403	1,399	1,037	519	157	1,404	391
Observations	69,645	68,409	46,721	22,804	46,841	22,924	65,453	21,886
R-squared	0.287	0.287	0.264	0.254	0.300	0.332	0.284	0.254

Notes. The table reports estimates of the baseline specification 2. The dependent variable is log(monthly earnings) in all columns. Regressions include cohort and degree fixed effects. Each column represents estimates on a different sample of degrees. Column (1) presents baseline estimates for reference. Columns (2)-(6) display estimates for samples defined by program size, while Columns (7) and (8) show estimates for samples defined by the proportion of students who completed their Bachelor's at the same institution. The sample includes women employed one year post-graduation with complete information on the dependent variables. Standard errors are clustered at the degree level, and all regressors are standardized.

Table 29: Robustness checks - Estimates of Peer Effects on Female Earnings Controlling for Other Peers' Characteristics

	Dependent variable: log(monthly earnings)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\hat{\delta}^{FP}$	0.041***	0.041***	0.040***	0.039***	0.039***	0.036***	0.040***	0.037***	0.037***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)
$\hat{\delta}^{MP}$	0.002	0.003	0.003	0.003	0.003	0.002	-0.000	-0.000	-0.000
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Share of peers with work. mother	✓								
Share of peers with high-SES mother		✓							
Share of peers with high-SES father			✓						
Share of peers with college educ mother				✓					
Share of peers with college educ father					✓				
Share of high-ability peers						✓			
Share of peers from academic track							✓		
Degree size								✓	
Share of female peers									✓
Degree FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Nb. of degrees	1,548	1,548	1,548	1,549	1,549	1,546	1,556	1,556	1,556
Observations	62,857	62,857	62,451	64,242	64,242	62,098	69,553	69,645	69,645
R-squared	0.293	0.293	0.293	0.291	0.291	0.292	0.288	0.287	0.288

Notes. The table presents estimates from the baseline specification 2 on log(monthly earnings). Each column represents a different regression, also controlling for alternative peer characteristics, disaggregated by gender. For instance, in Column 1, I control for the proportion of female and male peers with working mothers. The share of high-ability peers refer to the share of peers with Bachelor's grade above the median. All regressions account for cohort and degree fixed effects and are conducted on the sample of women employed one year post-graduation, with non-missing data on the relevant variables. Variation in sample size across columns results from missing values in certain covariates (from the institutional survey). Standard errors are clustered at the degree level, and all regressors are standardized.

Table 30: Robustness checks – Estimates of Peer Effects on Female Earnings Controlling for Geographical Characteristics

	Dependent variable: log(monthly earnings)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\hat{\delta}^{FP}$	0.035**	0.035***	0.040**	0.042***	0.036***	0.033	0.042***
	(0.015)	(0.013)	(0.017)	(0.013)	(0.012)	(0.023)	(0.015)
$\hat{\delta}^{MP}$	-0.005	-0.002	-0.009	-0.001	0.002	-0.001	0.005
	(0.012)	(0.010)	(0.013)	(0.010)	(0.010)	(0.018)	(0.012)
Per capita income in munic of female peers	✓						
Per capita income in munic of male peers	✓						
Size of munic of female peers		✓					
Size of munic of male peers		✓					
Big firms in prov of female peers			✓				
Big firms in prov male peers			✓				
Service sector in prov of female peers				✓			
Service sector in prov of male peers				✓			
Fertility rate in prov of female peers					✓		
Fertility rate in prov of male peers					✓		
MLFP in prov of female peers						✓	
MLFP in prov of male peers						✓	
Female education in prov of female peers							✓
Female education in prov of male peers							✓
Degree FE	✓	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓	✓
Observations	69,645	69,645	69,645	69,645	69,645	69,645	69,645
R-squared	0.288	0.288	0.287	0.288	0.288	0.287	0.288

Notes. The table presents estimates from the baseline specification 2 on log(monthly earnings), with added controls for alternative characteristics of peers' provinces. These characteristics are: per capita income and the number of inhabitants in the municipality of origin, the share of firms with over 50 employees, the share of firms in the service sector, fertility rate, the male labor force participation in the province of origin, and the proportion of women aged 19-34 with a high-school diploma. All these measures are standardized. Each column represents a different regression. All regressions account for cohort and degree fixed effects and are estimated on the sample of women employed one year post-graduation, with non-missing data on the relevant variables. Standard errors are clustered at the degree level.

Table 31: Robustness checks - Placebo Estimates Using Other Peers' Characteristics

	Dependent variable: log(monthly earnings)					
	(1)	(2)	(3)	(4)	(5)	(6)
MLFP in prov of female peers	0.032***					
	(0.012)					
MLFP in prov of male peers	0.000					
	(0.010)					
Service sector in prov of female peers		0.009				
		(0.010)				
Service sector in prov of male peers		-0.004				
		(0.007)				
Female education in prov of female peers			0.016			
			(0.011)			
Female education in prov of male peers			-0.003			
			(0.009)			
Fertility rate in prov of female peers				-0.006		
				(0.011)		
Fertility rate in prov of male peers				0.008		
				(0.008)		
Per capita income in munic of female peers					0.013*	
					(0.007)	
Per capita income in munic of male peers					0.004	
					(0.005)	
Size of munic of female peers						0.012
						(0.009)
Size of munic of male peers						0.007
						(0.007)
Degree FE	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓
Observations	69,645	69,645	69,645	69,645	69,645	69,645
R-squared	0.287	0.287	0.287	0.287	0.287	0.287

Notes. The table presents estimates from the baseline specification 2 on log(monthly earnings) using variation in alternative peers' characteristics. These characteristics are: per capita income and the number of inhabitants in the municipality of origin, the share of firms with over 50 employees, the share of firms in the service sector, fertility rate, the male labor force participation in the province of origin and the proportion of women aged 19-34 with a high-school diploma. All these measures are standardized. Each column represents a different regression. All regressions account for cohort and degree fixed effects and are estimated on the sample of women employed one year post-graduation, with non-missing data on the relevant variables. Standard errors are clustered at the degree level.

Table 32: Estimates of Peer Effects on Academic Performance and Migration Choices

	Panel A. Academic performance				Panel B. Migration			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GPA	Final grade	Time to completion	Pr(delayed grad.)	FLFP in prov. of work	Prov work = univ.	Reg work = univ.	Prov of work ≠ birth
(Mean)	(27.8)	(108.6)	(2.5)	(0.35)	(54.6)	(0.45)	(0.68)	(0.44)
δ^{FP}	0.047	0.071	-0.004	-0.007	0.155	0.007	0.013	0.007
	(0.029)	(0.102)	(0.010)	(0.008)	(0.151)	(0.011)	(0.011)	(0.010)
δ^{MP}	0.039	0.066	-0.006	-0.005	0.126	-0.010	-0.005	0.009
	(0.024)	(0.085)	(0.008)	(0.007)	(0.123)	(0.008)	(0.008)	(0.007)
Degree FE	✓	✓	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	182,792	182,792	182,792	182,792	66,102	66,102	66,102	66,102
R-squared	0.244	0.174	0.161	0.148	0.586	0.156	0.152	0.181

Notes. OLS estimates of a regression of indicators of academic performance on: the average FLFP in the provinces of origin of female and male peers and the FLFP in the own province of origin. Regressions include cohort and degree fixed effects. In Panel A, the dependent variables are: contemporaneous GPA (Column 1), final grade (Column 2), time to completion (Column 3), probability of delayed graduation (Column 4). In Panel B, the dependent variables are: FLFP in the province of employment (Column 5), an indicator of whether the province of employment is the same as that of the university attended (Column 6), an indicator of whether the region of employment matches the university's region (Column 7), and an indicator of whether the province of employment differs from the province of birth (Column 8). All the estimates are done on the full sample of women. All regressors are standardised. All regressors are standardised, while the dependent variables are not. The mean values of the dependent variables are provided in the table. Standard errors clustered at degree level.

Table 33: Estimates of Peer Effects on Female Earnings and Labor Supply Controlling for Share of Local Students

	(1) Log(monthly earnings)	(2) Log(weekly hours)	(3) Pr(fulltime)	(4) Log(hourly wage)
δ^{FP}	0.045***	0.041***	0.022**	0.003
	(0.013)	(0.012)	(0.010)	(0.013)
δ^{MP}	-0.002	-0.002	-0.001	-0.000
	(0.010)	(0.010)	(0.007)	(0.010)
Share of female stayers	-0.011*	-0.010*	-0.004	-0.000
	(0.006)	(0.006)	(0.004)	(0.005)
Share of male stayers	0.003	0.006	-0.001	-0.003
	(0.005)	(0.005)	(0.004)	(0.004)
Degree FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Observations	69,645	69,645	69,645	69,645
R-squared	0.288	0.246	0.280	0.100

Notes. OLS estimates of a regression of women's earnings and labor supply one year after graduation on: the average FLFP in the provinces of origin of female and male peers and the FLFP in the own province of origin, as well as the share of *local* female and male peers. A student is defined as *local* if she studies at university in her province of birth. Regressions include cohort and degree fixed effects. All the estimates are done on the sample of women employed one year post-graduation, with non-missing data on the relevant variables. Standard errors clustered at degree level. All regressors are standardised.

Table 34: Estimates of Peer Effects on Job-Search Preferences

	(1) Index Pecuniary	(2) Index Flexibility	(3) Job's social utility
δ^{FP}	0.003	-0.027*	-0.012*
	(0.009)	(0.015)	(0.007)
δ^{MP}	0.001	0.006	0.001
	(0.007)	(0.011)	(0.005)
Degree FE	✓	✓	✓
Cohort FE	✓	✓	✓
Observations	165,116	163,855	164,214
R-squared	0.089	0.043	0.093

Notes. OLS estimates of regressions of valuation of job attributes on: the average FLFP in the provinces of origin of female and male peers and the FLFP in the own province of origin. The dependent variables in Columns (1)-(3) measure the importance students place on different job characteristics. Answers come from the question: "How much do you value attribute X in the job you are searching?" (scale 1-5). Specifically, Column (1) reflects preferences for pecuniary job attributes, i.e., salary and career progression, based on a standardized index constructed from students' rankings on a 1-5 scale. The index in Column (2) is constructed by averaging students' rankings of job attributes related to flexibility (i.e., leisure time and hours flexibility). Both indexes in (1) and (2) have been standardised. The dependent variable in Column (3) is an indicator variable for whether a student gives maximum value to the social utility of a job. Regressions include cohort and degree fixed effects. The estimates are done on the sample of women who fill in the institutional pre-graduation survey (91.7%). Standard errors clustered at degree level. All regressors are standardised.

D Additional Tables from New Data Collection

Table 35: Main Characteristics of Female Students in the New Data Collection

	All			Low FLFP		High FLFP	
	Mean	SD	N	Mean	SD	Mean	SD
Background Characteristics							
Age	23.4	1.8	487	23.6	2.3	23.3	1.5
Changed province for Master (%)	88.8	31.6	490	100.0	0.0	82.6	37.9
Changed region for Master (%)	69.6	46.0	490	100.0	0.0	53.0	50.0
FLFP in province of origin	54.6	11.2	489	41.9	8.9	61.5	4.0
Mother: university level (%)	31.4	46.5	468	27.3	44.7	33.7	47.3
Father: university level (%)	28.0	44.9	465	32.7	47.1	25.3	43.6
Mother: full-time at childbirth (%)	49.9	50.1	465	45.7	50.0	52.2	50.0
Mother: part-time at childbirth (%)	30.1	45.9	465	23.2	42.3	33.9	47.4
Mother: no work at childbirth (%)	20.0	40.0	465	31.1	46.4	14.0	34.7
Field of study							
Major: Economics (%)	19.2	39.4	480	20.0	40.1	18.7	39.1
Major: Humanities (%)	45.2	49.8	480	40.0	49.1	48.1	50.0
Major: Science (%)	20.4	40.4	480	23.5	42.5	18.7	39.1
Major: Social Sciences (%)	15.2	35.9	480	16.5	37.2	14.5	35.3
First year (%)	65.1	47.7	490	61.8	48.7	66.9	47.1
Second year (%)	33.5	47.2	490	38.2	48.7	30.9	46.3
Above second year (%)	1.4	11.9	490	0.0	0.0	2.2	14.7
Civil Status and Fertility Expectations							
Single (%)	48.1	50.0	468	46.1	50.0	49.2	50.1
Has a partner (%)	46.4	49.9	468	48.5	50.1	45.2	49.9
Cohabits with partner (%)	5.6	22.9	468	5.5	22.8	5.6	23.1
Partner in same program (%)	3.4	18.2	468	2.4	15.4	4.0	19.5
Intend to have children (%)	54.0	49.9	470	52.7	50.1	54.8	49.9
Maybe children (%)	33.2	47.1	470	35.8	48.1	31.8	46.6
Does not intend to have children (%)	12.6	33.2	470	11.5	32.0	13.1	33.8
Has children already (%)	0.2	4.6	470	0.0	0.0	0.3	5.7
Expected age at first child	31.3	2.8	351	31.7	3.2	31.1	2.6
Intended Job Search							
Intend to search for a job (%)	79.7	40.3	488	80.8	39.5	79.1	40.7
Intend to pursue further education (%)	19.1	39.3	488	18.0	38.6	19.6	39.8
Intend to keep job (%)	1.2	11.0	488	1.2	10.8	1.3	11.2
Job location: North (%)	61.2	48.8	485	62.2	48.6	60.7	48.9
Job location: Centre (%)	15.7	36.4	485	14.0	34.8	16.6	37.3
Job location: South (%)	2.7	16.2	485	7.0	25.5	0.3	5.7
Job location: Abroad (%)	20.4	40.3	485	16.9	37.5	22.4	41.7

Notes. This table summarizes the main characteristics of the sample of prospective female students that participated in the data collection at the University of Bologna. It reports the mean and standard deviation of variables related to students' background, fields of study, civil status, partner information, fertility expectations, and labor market intentions. Statistics are shown for the overall sample (490 students), as well as for subsamples from above-median (317 students) and below-median (173 students) FLFP provinces.

Table 36: Baseline and Updated Beliefs on the Job Offer Distribution - Robustness

	Below-med FLFP		**Above-med FLFP**		
	Pred	SE	Pred	SE	P-value
a. Baseline Beliefs (T=0)					
α: Expected arrival rate of job offers (%)	32.30	1.80	35.05	1.26	0.23
γ_P: Expected % of part-time job offers	57.48	2.43	50.33	1.70	0.02
Perceived uncertainty (1-5)	2.80	0.13	2.93	0.09	0.44
Prob. to accept part-time job offer	67.26	2.17	59.66	1.50	0.01
b. Updated Beliefs (T=1)					
α: Expected arrival rate of job offers (%)	32.82	2.47	32.43	1.93	0.91
γ_P: Expected % of part-time job offers	52.41	3.11	51.89	2.43	0.90
Perceived uncertainty (1-5)	2.63	0.15	2.74	0.12	0.57
Prob. to accept part-time job offer	62.03	2.94	63.94	2.28	0.63

Notes. This table presents predictions from a linear regression model, where the dependent variable is regressed on an indicator for whether the FLFP in the birth province is above or below the median, along with fixed effects for the field of study and controls for students' background characteristics (age, parents' education), job search intentions, and expected job location. Each row represents a different regression, with the dependent variable specified in Column 1. For each regression, the table reports the predicted dependent variable for women from provinces with low versus high FLFP, along with the standard errors. The last column provides the p-value for the difference between these two groups. In Panel (a), the sample consists of all first-year female Master's students without missing information on the covariates (291), and in Panel (b), it includes all second-year female Master's students without missing information on the covariates (148). Between 60% and 65% of the students are from provinces with above-median FLFP.

Table 37: Acceptance of Part-time Jobs and Expectations on Job Offer Arrival Rates

	(1)	(2)	(3)	(4)
	Probability to accept part-time job offer			
Expected percentage of part-time offers (γ)	0.327**	0.272**		
	(0.066)	(0.056)		
Expected arrival rate of job offers (α)			-0.148**	-0.078
			(0.028)	(0.035)
Field FEs		✓		✓
Observations	463	463	464	464
R-squared	0.125	0.171	0.014	0.101

The table presents estimates from linear regressions of the likelihood of accepting a part-time job offer (intented) on workers' expected probability of receiving a job offer (Columns 1-2) or the expected percentage of part-time offers (Columns 3-4). In Columns 2 and 4, I include controls for the field of study. The sample consists of all female students with non-missing values for these variables, drawn from both the first and second year of the program.

Table 38: Baseline and Updated Expectations of Fertility and Future Labor Supply

	Below-med FLFP		**Above-med FLFP**		
	Pred	SE	Pred	SE	P-value
a. Baseline Expectations (T=0)					
Fertility: yes	0.50	0.05	0.54	0.04	0.50
Fertility: don't know	0.38	0.05	0.35	0.03	0.61
Fertility: no	0.12	0.03	0.11	0.02	0.76
Age of expected fertility	31.58	0.31	30.88	0.23	0.07
Labor supply at motherhood (Scenario 1)					
Work full-time	0.49	0.05	0.43	0.04	0.40
Work part-time	0.49	0.05	0.55	0.04	0.38
No work	0.03	0.02	0.03	0.02	0.90
Labor supply at motherhood (Scenario 2)					
Work full-time	0.70	0.05	0.68	0.04	0.81
Work part-time	0.28	0.05	0.31	0.04	0.58
No work	0.03	0.02	0.01	0.01	0.21
b. Updated Expectations (T=1)					
Fertility: yes	0.57	0.07	0.61	0.05	0.63
Fertility: don't know	0.32	0.06	0.23	0.04	0.27
Fertility: no	0.10	0.04	0.15	0.04	0.41
Age of expected fertility	32.65	0.44	31.13	0.35	**0.01**
Labor supply at motherhood (Scenario 1)					
Work full-time	0.67	0.06	0.41	0.06	**0.00**
Work part-time	0.33	0.06	0.55	0.06	**0.02**
No work	0.04	0.03			
Labor supply at motherhood (Scenario 2)					
Work full-time	0.79	0.05	0.80	0.05	0.85
Work part-time	0.21	0.05	0.20	0.05	0.85
No work	0.00		0.00		

Notes. This table presents predictions from logistic regressions, where the dependent variable is regressed on an indicator for whether the FLFP in the birth province is above or below the median, along with fixed effects for the field of study. Each row represents a different regression, with the dependent variable specified in Column 1. For each regression, the table reports the predicted dependent variable for women from provinces with low versus high FLFP, along with the standard errors. The last column provides the p-value for the difference between these two groups. In Panel (a), the sample consists of all first-year female Master's students without missing information on the dependent variables, and in Panel (b), it includes all second-year female Master's students without missing information on the dependent variables. Between 60% and 65% of the students are from provinces with above-median FLFP.

Table 39: Baseline and Updated Attitudes

	Below-med FLFP		**Above-med FLFP**		
	Pred	SE	Pred	SE	P-value
Baseline Beliefs (T=0)					
Employers' discrimination					
Strongly disagree	0.03	0.02	0.02	0.01	0.55
Disagree	0.04	0.02	0.15	0.03	0.00
Agree	0.65	0.05	0.56	0.04	0.12
Strongly agree	0.27	0.05	0.26	0.03	0.78
Ambition is negatively judged					
Strongly disagree	0.08	0.03	0.04	0.01	0.23
Disagree	0.21	0.04	0.28	0.03	0.21
Agree	0.42	0.05	0.46	0.04	0.54
Strongly agree	0.28	0.04	0.21	0.03	0.16
Updated Beliefs (T=1)					
Employers' discrimination					
Strongly disagree					
Disagree	0.13	0.05	0.12	0.03	0.87
Agree	0.50	0.07	0.57	0.05	0.41
Strongly agree	0.36	0.06	0.31	0.05	0.57
Ambition is negatively judged					
Strongly disagree	0.03	0.02	0.05	0.02	0.49
Disagree	0.14	0.05	0.25	0.05	0.12
Agree	0.48	0.07	0.41	0.05	0.43
Strongly agree	0.35	0.07	0.28	0.05	0.42

Notes. This table presents predictions from a linear probability model, where the dependent variable (agreement with one of the statements) is regressed on an indicator for whether the FLFP in the birth province is above or below the median, along with fixed effects for the field of study. Each row represents a different regression, with the dependent variable specified in Column 1. The statements to which students should express agreement with are "Employers prefer to hire men for full-time positions" and "A woman is negatively judged if she is too ambitious". In the upper panel, the sample comprises all first-year female Master's students without missing information on the dependent variables, and in the lower panel, it includes all second-year female Master's students without missing information on the dependent variables. Between 60% and 65% of the students in the two cohorts are from provinces with above-median FLFP.