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

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Abstract

Gender norms are widely recognized as key determinants of persistent gender gaps in the labor market, yet our understanding of their drivers remains limited. This paper addresses this gap by examining how cultural assimilation from college peers influences women's early-career labor market decisions. I leverage idiosyncratic cross-cohort variation in peers' geographical origins within Master's programs, combined with unique administrative and survey data covering the universe of students in Italy. The main finding is that exposure to female classmates born in areas with a more egalitarian gender culture significantly increases women's labor supply, primarily through increased uptake of full-time jobs. Specifically, socialization with peers from areas with a one standard deviation higher female labor force participation offsets much of the negative impact of limited female role models in childhood, resulting in a 21-40% decrease in early-career gender gaps. Using original data on students' beliefs that I collected, I find that decreases in women's valuation of work hours flexibility, coupled with learning about the job offer distribution primarily drive the observed effects. Since peer effects are highly asymmetric, with benefits concentrated among women from less egalitarian backgrounds, education policies that promote diversity could play a crucial role in shifting gender norms and advancing gender equality in the labor market.

JEL classification: J31, J16, J22, R0, Z13.

Keywords: gender gaps, female labor supply, job search, peer effects, biased beliefs, gender norms.

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1 INTRODUCTION

Cultural norms are ubiquitous and shape payoffs from many individual decisions. One critical area where their influence is particularly strong is in the economic decisions of men and women. By shaping the beliefs and preferences of both genders, gender norms are recognized as key determinants of the persistent gender gaps in the labor market, over and above traditional economic factors such as human capital accumulation, comparative advantage and discrimination (Bertrand (2020), Giuliano (2020), Cortes and Pan (2023)). Even in a world where adhering to gender norms has become increasingly costly, their long-term 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 a few studies have investigated the intergenerational transmission of gender norms (Fogli and Veldkamp (2011), Fernandez (2013)), most of the literature has focused on documenting their persistence, with little attention paid to the role of factors such as peers and public policies in shaping their evolution. This is primarily due to the paucity of suitable settings and of data sources that allow analyzing empirically how gender norms are transmitted.

This paper addresses this gap by providing the first causal evidence on the role of college classmates in shaping the transmission of gender norms. Specifically, I investigate how exogenous exposure to peers from more egalitarian areas affects women's early-career decisions. By combining estimates of peer and childhood exposure effects, I assess the relative importance of these channels in the transmission of gender norms. The analysis is grounded in comprehensive administrative and survey data covering 93% of Italian students, complemented by innovative data on job-search preferences and beliefs.

Italy offers an ideal setting to study gender norms and how peers shape their evolution. Owing to (i) granular yet substantial variation in gender culture across areas, and (ii) high mobility rates of students outside their birth place (57%), universities create a melting pot, bringing together students from regions with markedly different gender norms into small Master's programs. Heterogeneity in gender culture across provinces is striking: for example, the ratio of female to male labor force participation varies from 43% to 86%

across provinces, a disparity within a single country that mirrors the scale of wide cross-country differences.[1] Moreover, the small cohort sizes in Master's programs (median of 34 students) and the two-year duration of shared study create an environment conducive to close social interactions, as confirmed by students' survey responses.

I start by establishing that childhood exposure to gender norms has a lasting influence on women's labor supply decisions at the start of their careers—a phenomenon I refer to as *cultural persistence*. Building on the epidemiological approach of Fernandez (2007), the effect of early cultural exposure is estimated based on the relationship between the labor supply decisions of movers—individuals working in a province different from their birthplace- and various measures of gender culture in their place of birth.[2] These measures include standard indicators, such as female labor force participation (FLFP) relative to men, as well as novel indicators including firms' gender culture, or the labor supply of previous cohorts of graduates drawn from the behavior of stayers in the sample. I find that women who move from more gender-egalitarian areas have significantly higher labor supply compared to similar peers born in less egalitarian provinces. This pattern holds when controlling for factors such as working in the same local labor market and graduating from the same Master's program with similar academic performance. The observed difference is both statistically significant and economically meaningful, translating into a 7.6% increase in weekly hours worked or in a 6.2% increase in net earnings. I show that this relationship is unlikely driven by differential selection of movers from different areas.

What impact does exposure to peers from different cultural backgrounds have on women's labor supply decisions? To address this question, I exploit within-degree, between cohort variation in exposure to peers from more egalitarian areas across five cohorts of university students (Hoxby (2000)). This is possible due to availability of longitudinal data allowing me to track how peer composition evolves over time across 1,572 Master's programs—a key advantage over traditional data sources, which are often limited to smaller samples. While most of the variation in peers' geographical origins occurs across different programs, Master's programs are small enough to offer meaningful within-

[1] These disparities in labor force participation align closely with regional differences in gender attitudes, firms' gender culture, and other measures discussed in detail in the paper.

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

program variation over time.[3] For this identification strategy to be valid, this variation must be orthogonal to time-varying, unobserved determinants of labor market outcomes. I probe the validity of this assumption through an extensive set of traditional and newly proposed randomization checks.[4]

My main finding is that socialization with female classmates who grew up in provinces with more egalitarian gender norms significantly increases women's labor supply along the intensive margin, leading to a higher take-up of full-time jobs. The magnitude of this effect is large: exposure to female peers from areas with a one standard deviation higher female labor force participation (8.5 percentage points) leads to a 3.3% increase in weekly hours and in a 1.9 percentage point increase in the likelihood of full-time employment one year after graduation, translating to a 3.7% increase in net monthly earnings.[5] Around one third of the increase in women's labor supply is associated with greater sorting into occupations with higher earnings and a larger share of full-time jobs. In contrast, peer exposure does not affect men outcomes, irrespective of the gender of their peers. Given the lack of influence on men, the estimated peer effects for women are economically significant, narrowing gender gaps in these outcomes by 21–40%.

A key advantage of this setting is that it enables a direct comparison of the relative impacts of childhood exposure and peer effects. One central finding is the marked asymmetry in peer effects: exposure to classmates with more egalitarian gender norms makes women from areas with below-median FLFP more likely to enter full-time jobs, yet it has no observable effect on the choices of women who grew up in higher FLFP provinces. Due to this asymmetry, peer influence mitigate a substantial portion of the initial disadvantage faced by women from less egalitarian areas, suggesting that college classmates can help counteract the adverse effects of limited role models encountered during childhood. These findings carry important policy implications, indicating that education policies promot-

[3]Because many degrees are selective, this variation arises from fluctuations in the geographic origins of students whose scores meet admission criteria, hence should be considered as conditional on students' ability.

[4]These include a battery of balancing tests verifying that within-degree variation in the geographical origins of students is not related to changes in students' background characteristics, including prior academic records, family background, educational history, and socio-demographic characteristics. The identifying variation appears consistent with random fluctuations, based on a series of simulations. Other checks include dropping programs experiencing plausibly non-random changes in size and in the distribution of students' ability, and adding degree- or region-specific linear trends.

[5]Estimates range from 3.5–4.1% across alternative measures of gender norms in peers' provinces. These results are robust to controls for other geographic characteristics unrelated to gender, such as income per capita, male labor force participation, fertility rates, etc.

ing diversity could play a crucial role in breaking the persistence of gender norms and advancing gender equality in the labor market.

Identifying the precise mechanisms through which peer effects operate has long been a challenge, primarily due to data limitations (Sacerdote (2011)). Yet understanding these mechanisms is crucial for designing policies that can replicate the benefits of peer exposure without altering peer group composition (Barrios Fernandez (2023)). With innovative data, this paper advances our understanding by identifying two channels. First, leveraging comprehensive data on students' job-search preferences collected through a compulsory pre-graduation survey, I show that exposure to female peers from more egalitarian areas leads to a reduction in the perceived importance of non-pecuniary job attributes—particularly those related to temporal flexibility and the social value of a job. Previous research has underscored the importance of gender differences in the valuation of job attributes in explaining substantial portions of the gender earnings gap.[6] I add to these findings by showing that these preferences are endogenous to the social environment and shaped by gender norms.

A second channel is information diffusion through peer interactions. The design of a novel survey enabled me to examine a wide array of beliefs possibly related to the decision of accepting part-time jobs. These include beliefs about gender roles, expectations of fertility and future labor supply, perceptions of employers' discrimination, as well as expectations about job offer arrival rates and other key parameters of a job-search model. The survey was administered in person in fall 2023 to two consecutive cohorts of Master's students at one large university.[7]

I use students' responses at the start of their first year to examine heterogeneity in baseline beliefs associated with FLFP (and related measures) in their home provinces. I uncover one striking asymmetry: women from high- and low-FLFP areas systematically differ in their expectations regarding job offer arrival rates, aligning with qualitative evidence gathered from interviews. Specifically, for a given level of job-search effort and for positions aligned with their degree-specific skills, women from low-FLFP areas expect

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

[7]In-class administration, combined with lottery incentives, resulted in a 97% response rate among attending students.

to receive 13% fewer full-time job offers than their peers from high-FLFP areas seeking work in the same location.[8] By eliciting beliefs directly on the primitives, these should be interpreted as reflecting expectations about the demand side of the labor market rather than their job-search effort. In line with the predictions of a McCall-type model (McCall (1970)) incorporating heterogeneous beliefs, I find that these beliefs strongly predict part-time job acceptance, accounting for roughly one-fifth of the difference between women from high- and low-FLFP areas. Asymmetric belief updating over the first year—with women from low-FLFP areas adjusting their expectations to converge with those of their peers—narrows the initial gap in these beliefs by 70%, in line with social learning.

Related literature. This article contributes to three lines of research. First, it relates to a burgeoning literature that, building on the epidemiological approach of Fernandez (2007), documents the persistence of gender norms, showing that early cultural exposure shape women's labor supply decisions in adulthood, especially around motherhood (Antecol (2000), Fernandez and Fogli (2009), Blau et al. (2011), Fortin (2015), Bertrand et al. (2015), Cortés et al. (2022a), Ichino et al. (2024)), Kleven (2024), Boelman et al. (Forthcoming)). By focussing on a narrower segment—young, educated women—my findings add to this literature by showing that childhood exposure to gender norms affects women's labor supply choices already at the very start of their careers, a channel that may determine more pronounced reductions in labor supply later in life. Second, I uncover a novel channel behind cultural persistence: by observing the labor market participation of women in their home regions, women form beliefs about the likelihood of receiving job offers. Asymmetries in beliefs among workers lead to differences in economic outcomes in a self-fulfilling way. With this finding, I extend the conventional view of cultural persistence beyond preferences and attitudes, and show that information frictions may also play a key role.[9] This finding suggests that information provision can be effective in altering gender norms and reducing gender disparities.

[8]These correlate with different perceptions of employers' discrimination in the allocation of full-time jobs, elicited with qualitative questions. On the contrary, no significant differences are observed in fertility expectations or intended labor supply after motherhood, potentially because such differences emerge later (Kuziemko et al. (2018)).

[9]These findings complement those of Bursztyn et al. (2020) and Cortés et al. (2022b), who highlighted the role of biases in second-order beliefs in perpetuating the stickiness of gender norms.

A second strand focuses on the transmission of gender norms. The literature has started to study cultural change from an intergenerational perspective, using models of social learning. Fogli and Veldkamp (2011) and Fernandez (2013) model a process in which beliefs evolve by observing nearby employed women. As more women participate in the labor force, information diffuses, leading to belief updating and increased participation among younger cohorts of women. Empirical support for this channel comes from Olivetti et al. (2020), Mertz et al. (2024) and Kleven et al. (2024), who show that women's career decisions (such as working in motherhood or occupational choices) are influenced by maternal role models observed among peers' mothers during childhood and adolescence. An emerging and directly related literature examines the "horizontal transmission" of norms, focusing on the influence of coworkers (Boelman et al. (Forthcoming)) and neighbors (Maurin and Moschion (2009), Jessen et al. (2024)). My study contributes to this literature in two ways. First, to the best of my knowledge, this paper provides the first large-scale evidence on the critical role of college classmates in the transmission of gender norms. Exploiting exogeneous variation in peer composition, I show that socialization with female peers from areas with a one-sd higher FLFP can offset most of the negative effects of limited female role models during childhood, resulting in substantial decrease in gender gaps. This challenges the notion that gender norms are primarily formed in early childhood and remain sticky over time, aligning with the findings of Giavazzi et al. (2019). Second, my work advances the understanding of the driving forces of peer influence. Using innovative data sources, I show that these effects are primarily driven by social learning and changes in women's job-search preferences.

A third strand is the nascent but fast-growing literature that examines how job seekers' misperceptions about their own prospects affect job-search behavior. While standard job-search models typically assume rational expectations, recent evidence points to significant biases in workers' beliefs (see Mueller and Spinnewijn (2023) for a review). Studies across both high- and low-income settings reveal that unemployed job seekers tend to be overly optimistic about 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)). Additional biases in perceptions of re-employment wages and outside options have also been documented (Drahs et al. (2018), Cortes et al. (2023), Alfonsi et al. (2024), Jäger et al. (2024)). Although evaluating the impact of these biases on job-search behavior is challenging, many studies find that these beliefs are highly predictive of actual outcomes. This paper investigates workers' beliefs about the arrival rates of part-time and full-time job offers. Unlike most previous studies, my elicitation method holds workers' search effort constant, allowing me to isolate expectations related to the demand side of the labor market. I contribute to this literature by documenting significant heterogeneity in these beliefs among workers from different local labor markets. Specifically, I find that a portion of the variation in part-time job acceptance rates between women from high- and low-FLFP regions can be attributed to the latter group's more pessimistic beliefs about the likelihood of being offered a full-time position. Finally, I explore learning and provide evidence that peers likely play a crucial role in the rapid belief updating of women disposing of limited initial information.

The article is organized as follows. Section 2 describes the institutional setting and the data sources. Section 3 describes the melting pot at Italian universities. Section 4 presents the early-career gender earnings gap and estimates of *cultural persistence*. Section 5 presents the identification strategy and examines its validity. Section 6 shows estimates of peer effects. Section 7 examines the robustness and sensitivity of the estimates across alternative specifications and samples. Section 8 explores non-linearities in peer effects. Section 9 analyzes the mechanisms. Section 10 deepens the understanding of cultural persistence and social learning with new survey data on beliefs. Section 11 concludes and discusses education policies.

2 Institutional Background and Data

2.1 Admission and Structure of Graduate Education in Italy

Admission to Master's programs. Since the early 2000s, university programs in Italy have been organized into bachelor's (three years) and master's (two years) degrees.[10] Approximately 70% of students pursue a two-year master's program after completing their bachelor's. Admission to a master's program typically involves meeting specific curricular prerequisites, such as credits in required courses. This system allows students

[10] Italy adheres to the Bologna process (1999) that ensures comparability in higher education standards across the European Higher Education Area (EHEA), comprising 48 European and Central Asian countries.

some flexibility to switch fields between their undergraduate and master's studies, provided they meet the relevant eligibility criteria.[11] In addition to these prerequisites, many programs also include selective entry exams, bachelor's grade requirements, and interviews as part of their admission process. Admission is often competitive, with applicants ranked based on entry exam scores or bachelor's GPA. Additional requirements, such as English proficiency, motivation letters, or reference letters, may also apply. Such criteria are autonomously determined by academic institutions. Only in certain fields—such as medicine, health sciences, architecture, psychology, and primary education—admission is based on a selective national entry exam. Throughout this paper, I use the following terminology: a *degree* refers to a master's program within a specific university; a university *course* is a specific subject studied within a degree, corresponding to a given number of credits; and a *field of study* refers to a discipline (e.g., economics) that can be offered at several universities.

Tuition fees. Approximately 90% of all students attend public universities (ISTAT (2016)), where tuition fees vary depending on the degree, institution, and family income. Regional governments set income thresholds for need-based grants, which cover tuition, housing, and meal vouchers (Rattini (2022)). On average, 23% of the students in my sample receive such grants. or those not eligible, the average annual tuition fee is €1,262 (Commission/EACEA/Eurydice (2016)).

2.2 Data Sources and Sample

The empirical analysis draws on several data sources. I use comprehensive administrative data from university records covering 93% of students in Italy. This includes students from most public universities and a subset of private universities that are part of the AlmaLaurea consortium. These records are linked to pre-graduation institutional survey data and post-graduation follow-up surveys conducted by the AlmaLaurea consortium, allowing to track students' career trajectories during the first five years after graduation and to gain detailed information on their job-search process and preferences. Additionally,

[11] On average, students must complete 77 constrained credits to qualify for a master's program, though requirements vary across fields. For example, a student entering a master's program in economics must have earned at least 53 credits in economics, statistics, or other social sciences (Brandimarti (2023)).

I have designed a longitudinal survey to collect a wide array of students' beliefs over time.

Administrative student-level data. These data come from university records and include information on academic performance during the master's program (number of exams, GPA, and final grade), high-school education (school type, grades), demographic information (age, immigration status, municipality of birth and residence), as well as unique identifiers for master's programs within universities, and students' enrollment and graduation dates. Importantly, I use this data to identify peers and construct measures of their gender culture based on their birth or residence province. Due to the administrative nature of the data, all information is available for the entire student population, ensuring that I can observe the characteristics of all peers.

Institutional pre-graduation survey. These data come from a survey administered by universities to all graduating students as part of the graduation process. At the end of their final year, once they have passed all exams, students are required to complete this compulsory survey, resulting in a response rate close to 100%.[12] The survey collects detailed information on students' job search intentions and preferences, including their valuation of various job attributes. It also gathers data on students' socio-economic backgrounds, such as their parents' occupations and education levels. Additionally, the survey provides detailed information on students' educational histories, including their high school and bachelor's degree education, their previous grades, and any work activities undertaken during their studies.

Follow-up surveys. Follow-up surveys are conducted by the AlmaLaurea consortium one, three, and five years after graduation. Because the cohorts of students in my sample are recent, I rely on the survey after one year. Students are initially contacted by email and, if necessary, by phone, resulting in high response rates. One year after graduation, the response rates are 73.7% for women and 73.2% for men (Table A.2).[13] These surveys collect

[12] Students may choose to leave the questionnaire blank or decline to authorize the use of their data for research purposes. However, more than 90% of students effectively complete the survey and give consent for their data to be used.

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

comprehensive information on job characteristics, such as net monthly earnings, usual weekly hours worked (including extra hours), contract type (part-time vs. full-time), job security, occupation, industry, sector, and location. Responses to questions about earnings and usual weekly hours worked are collected in discrete bins, which I convert into continuous variables by assigning the midpoint of each bin.[14] Additionally, the surveys include retrospective information on the job-search process and current job-search activities.

Survey on students' beliefs. Understanding the mechanisms of peer influence has been challenging so far, primarily due to data limitations. To address this, I designed an original survey to elicit students' beliefs about gender attitudes and various future outcomes. These include perceptions of employer discrimination, expectations regarding their own job prospects and parameters of a job-search model, as well as expectations about future fertility and labor supply. The survey also collects data on the network structure and perceived peer influence. It was administered in fall 2023 to two cohorts of students in a sample of master's programs at one large university. With in-person administration and lottery incentives, I achieved a 97% response rate among attending students. Detailed information on the survey and elicitation methods is provided in Section 10. In this Section, I will also discuss the main insights from a set of 30-minutes interviews I have conducted on students from several universities.

2.3 Sample description

In this paper, I focus on students enrolled between 2012 and 2016.[15] The sample is restricted to master's degree programs that (i) have at least one man and one woman enrolled in the same cohort and (ii) meet this criterion for at least two consecutive years. These restrictions exclude degrees accounting for 3.55% and 6% of students, respectively. The final analysis sample comprises 316,470 students from 1,572 degree programs across

[14]Possible answers to the earnings question were < €250, €250–€500, €500–€750, €750–€1000, €1000–€1250, €1250–€1500, €1500–€1750, €1750–€2000, €2000–€2250, €2250–€2500, €2500–€3000, and > €3000. I converted the answers into a real-valued earnings variable at the mid-point of each earnings bin; I assigned earnings of €187,5 to those that responded earning less than €250 and earnings of €3750 to those who indicated earning more than €3000. The response bins for usual weekly hours worked were < 5 hours, 5-9 hours, 10-14 hours, 15-19 hours, 20-24 hours, 25-29 hours, 30-34 hours, . . . , 55-59 hours, and > 60 hours.

[15]Since data are linked based on graduating cohorts, I recostruct enrollment cohorts using students' enrollment and graduation dates from university records.

71 universities, including 182,792 women and 133,678 men. Importantly, the sample only includes students who remained enrolled for the full duration of their master's program.[16]

Background characteristics and academic records. Table A.1 provides descriptive statistics on background characteristics and academic performance in the sample, disaggregated by student gender. The last column of the tables reports the p-value for the test of equality of means between female and male students. These data are drawn from both administrative records and the institutional survey (the latter is available for 91% of students).

On average, women outperform men academically, as evidenced by higher GPAs and final grades during their master's studies, as well as stronger prior academic records, such as bachelor's and high school grades. Women are also more likely to have attended the academic high-school track, as opposed to technical or vocational tracks, (*liceo*) than men—84.2% versus 71.4%. The variation in these outcomes is also smaller among women compared to men. In terms of field specialization, women are less likely to chose scientific tracks and more concentrated in humanities, both in high school and at university. The largest disparities are in engineering and humanities: 27% of men study engineering, compared to just 8.2% of women, while 24.7% of women and only 10.4% of men pursue humanities. An equally high share of female and male students study science, chemistry, or biology at university (around 13%). Regarding family background, around one-fifth of female students have parents with tertiary education, and roughly one-third come from families where the father is in a high-SES profession, defined based on occupations. Male students are more likely to come from wealthier backgrounds, as indicated by a higher share of parents with tertiary education and a greater proportion of parents in high-SES occupations. While all fathers are in the labor force, the labor force participation rate of mothers falls to 71% and 73% (a significantly higher share than the national average).

Labor market outcomes and the job-search process. Table A.2 provides summary statistics of labor market outcomes, based on responses from the follow-up survey conducted one year after graduation. Response rates to this survey are 73.7% and 73.2% in the samples of women and men, respectively. At the time of the survey, around 12% of both

[16] A drawback of this approach is that I lose track of dropouts, who account for 6% of enrolled students between 2012 and 2016 (ANVUR (2023)).

female and male students are pursuing further education, either at the master's or PhD level, while the majority are part of the labor force. Among respondents, 66.6% of women and 71.3% of men are employed, either with a standard labor contract 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. These gender differences in labor market outcomes are attributable to differences in field specialization, as I will discuss in Section 4.

Among employed graduates, women face less favorable outcomes than men. On average, women earn €1,077.8 per month, while men earn €1,324. Despite the fact that the vast majority of women (93.6%) express a preference for full-time positions, as indicated in the institutional survey[17], 30.7% of women are employed part-time, compared to only 13.8% of men. Women are also underrepresented in occupations and industries that offer above-median earnings or a higher proportion of full-time jobs. A larger share of women work in the public sector (16.5% vs. 11% for men) and are less likely to hold permanent contracts. Additionally, women are twice as likely as men to work without any contract.

In terms of the job-search process, more than 80% of both men and women are in their first job post-graduation, though women have had a slightly higher number of jobs, suggesting that their contracts tend to be of shorter duration. Most graduates begin their job search within the first month after graduation, and, on average, women accept their first job offer within 3 months, compared to 2.7 months for men.[18] Women also report being less satisfied with their job outcomes, as reflected in a higher rate of on-the-job search. Notably, women are almost twice as likely to seek another job when employed part-time versus full-time—58% of part-time employed women engage in job searches, compared to only 30.8% of full-time employed women—suggesting greater dissatisfaction with part-time positions. Additionally, women are more likely to experience greater skill mismatch than men, as indicated by lower shares utilizing the skills acquired during their master's. Overall, women report lower levels of job satisfaction than men.

[17] Preference for full-time jobs is determined 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?" Students could answer on a scale from "Not at all" to "Absolutely yes." Those more inclined to accept a full-time than a part-time position are classified as preferring full-time work.

[18] This variable measures the number of months after graduation that a student begins searching for a job, with "0" representing those who began their search before or immediately after graduating.

3 THE COLLEGE MELTING POT

This section outlines three distinctive features of the Italian higher education system that make it particularly well-suited for studying cultural assimilation from college classmates. Italian universities can be seen as a "melting pot", where students raised in areas with very different gender norms come together within relatively small Master's programs. These programs, lasting at least two years, therefore offer an environment of close interactions among students from diverse cultural backgrounds, providing a unique opportunity to examine how peer exposure shapes beliefs and behaviors.

3.1 HETEROGENEITY IN GENDER CULTURE ACROSS BIRTH PROVINCES

Studying cultural assimilation first requires significant variation in gender norms. Italy provides an ideal setting, offering granular yet wide variations in gender culture across provinces.[19] One key feature is the substantial geographical heterogeneity in women's labor market outcomes. For example, the ratio of female to male labor force participation (FLFP/MLFP) ranges between 43% and 86%. These disparities in participation closely track regional differences in gender attitudes. For example, 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 (1990-2008)). The scale of these regional differences is comparable to cross-country variations.

In this paper, I consider several alternative measures of gender culture, all defined at the geographical level:

1. Female labor force participation (FLFP hereafter) of different age groups, at the province level;
2. Ratio of female to male labor force participation (FLFP/MLFP hereafter) of different age groups, at the province level;
3. Percentage of firms in the private sector without hiring preferences for male workers, at the province level;

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

4. Percentage of female college graduates that are employed full-time at the outset of the career, at the region level;

5. Percentage of female vs. male college graduates that are employed full-time at the outset of the career, at the region level;

6. Historical literacy rates of women vs. men, at the province level.

Most of these indicators are defined at the province level (NUTS-3 classification). Italy is divided into 103 provinces, which are administrative units between municipalities and regions.[20] Students are assigned to provinces based on their residence at the time of enrollment, as recorded in university registers. Such province should be interpreted as the place where the student was born and raised (for 80% of the sample, the province of residence and birth coincide). Since these measures are intended to proxy for the gender norms that students were exposed to early in life, they are measured prior to university enrollment, especially during adolescence.

The first two measures, which are traditionally used to proxy for gender culture, refer to averages of FLFP and FLFP/MLFP from 2004 to 2007. Indicators of firms' gender culture in (3) are constructed based on answers to a nationally representative survey of 100,000 Italian firms in 2003 (*Indagine Excelsior, Unioncamere*[21]). Each year, firms report their hiring intentions, specifying whether they prefer to hire male or female workers, or if they have no preference between the two sexes. At the province level, I define firms' gender culture as the percentage of firms that either prefer female workers or are indifferent between male and female hires. I also rely on measures of full-time employment of previous cohorts of female graduates, who may serve as a more relevant reference group for the students in the sample. To construct measures (4) and (5), I map local labor market opportunities for female and male college graduates, focusing on graduates who remain employed in their province of birth. Using labor market data from cohorts preceding those analyzed, I

[20] As of 2010, the average population of a province was 551,000, though there is significant variation. The largest, 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.

[21] Starting from 1997, the Excelsior Survey represents one of the main sources of information on the Italian labor market. The survey is administered by Unioncamere, in partnership with the Ministry of Labor, ANPAL and the European Union. The survey is conducted on firms operating in the manufacturing and service sectors with at least 0.5 employees/year. It excludes employers in the agricultural and public sector, as well as those that are not registered with the Chambers of Commerce. The sample of firms represents roughly one third of the total in the respective population.

calculate the % of female college graduates employed full-time one year after graduation, both in absolute terms and relative to male graduates. Due to limited data in smaller provinces, these measures are aggregated at the regional level (NUTS 2). Finally, I rely on historical proxy of gender culture, given by the ratio between the female and male literacy rates in 1911 drawn from the Italian Census data.

Summary statistics. Table 1 shows descriptive statistics for these different indicators in the sample. Table A.3 disaggregates these statistics by gender, showing that there are no significant differences in the geographical origins of female and male graduates. Figure A.1 visually illustrates the spatial distribution of some of these measures across provinces. All of the measures reveal substantial variation across provinces.

TABLE 1. Summary statistics of measures of gender culture in the sample

Variable	Mean	SD	Min	Max	Obs
Female labor force participation (age: 15-64)	49.7	11.2	27.3	66.7	316470
Female/Male labor force participation (age: 15-64)	66.7	11.8	43.0	85.7	316470
Female labor force participation (age: 25-34)	65.1	15.2	38.0	86.0	316470
Female/Male labor force participation (age: 25-34)	74.3	13.0	47.0	95.0	316470
Male labor force participation (age: 15-64)	73.8	4.5	62.9	81.9	316470
Male labor force participation (age: 25-34)	86.7	6.5	71.4	97.1	316470
% of female graduates in full-time job	56.4	9.5	40.1	68.9	316470
% of female/male graduates in full-time job	71.8	6.7	55.3	83.5	316470
% of firms without hiring pref. for male workers	54.3	8.9	35.0	71.0	316470
Historical literacy rates of female/male	81.7	13.1	54.0	100.0	316470

Notes. The Table presents summary statistics of the measures of gender culture 1-5 presented in Section 3. The unit of observation is a student. Students are assigned to provinces based on their residence province prior to enrollment in the Master.

For instance, FLFP varies widely across regions, with some areas seeing rates as low as 27%—comparable to rates in low-income countries—while others exceed the OECD average. These disparities are similarly stark among young women (ages 25-34), where FLFP ranges from 38% to 86%. Importantly, these differences are not solely reflections of general labor market conditions. The FLFP/MLFP ratio, which also varies widely, highlights the gender-specific nature of these trends: for all women, this ratio ranges from 43% to 86%, while for young women, it spans from 47% to 95%. MLFP also varies geographically but with a range less than half as wide as that for FLFP. Significant differences emerge across other labor market indicators as well. For example, the female-to-male ratio of college graduates in full-time employment varies between 55% and 83%, and the share of firms expressing no preference for male workers in hiring ranges from 35% to 71%.

Table A.5 provides pairwise correlations between measures of gender culture and other characteristics of provinces, for which summary statistics are provided in Table A.4. FLFP correlates strongly with other geographical factors, in particular MLFP, per-capita income, and childcare availability. Given these strong associations, Section 7.3 will aim to disentangle the specific influence of gender culture from these other factors.

3.2 Mobility outside birth provinces

Within this context, a second key aspect is the high mobility of students who study outside their home province. Due to historical and institutional factors, the majority of students in Italy relocate to attend university (ANVUR (2023)). This phenomenon has longstanding origins and has been relatively stable over time. During the period covered by this analysis, more than 57% of students moved to another province, and about 31% moved to a different region to pursue higher education. To better understand the strong migration of students away from their province of origin, it is useful to describe the institutional landscape in Italy. In 2016, public universities, which account for over 90% of students, offered Master's degrees at 89 institutions. However, these universities were concentrated in only 52 of Italy's 103 provinces. Furthermore, not all fields of study are available at every institution, as some universities specialize in specific disciplines.[22] Approximately 20% of Italians aged 18-19 live in provinces without higher education institutions, and only 77% have access to both STEM and non-STEM universities within their home province (Braccioli et al. (2023)). Additionally, students can apply to any university in the country, regardless of their residence. These factors, along with regional differences in post-graduation opportunities, contribute to the high levels of student mobility seen across the country.

Mobility patterns in the sample. Table A.6 describes students' mobility by gender. 58.9% of women 55.4% of men have moved outside their birth province for their studies. Overall,

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

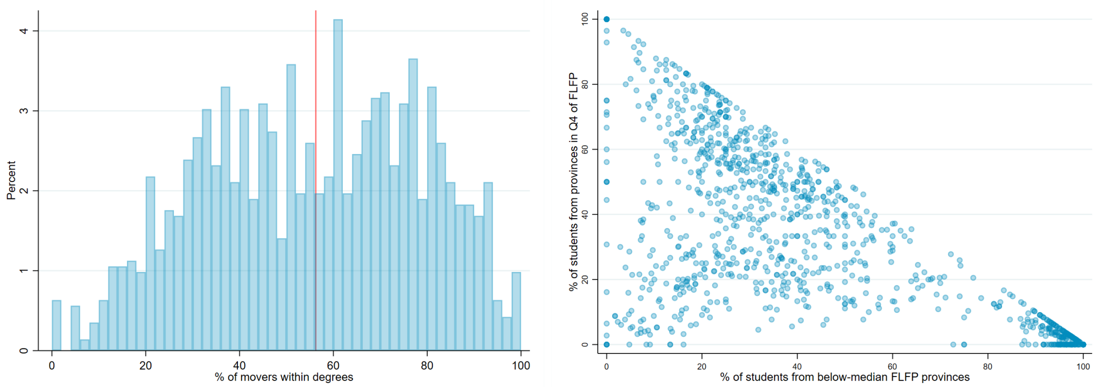
the mobility destinations for both genders do not exhibit significant differences, with both groups studying in areas characterized by more egalitarian gender culture compared to their provinces of origin. Movers are distributed across all degrees: less than 1% of programs have no movers, while 50% of degrees have more than 56% of movers, as represented in Figure 1 (Panel (A)).

Additionally, Table A.7 provides summary statistics on mobility patterns to local labor markets for students employed at the time of the follow-up survey. A large proportion of students work outside their province of origin, with this share being higher for male students (51.4%, compared to 44% for women), indicating that women are more likely to return to their home provinces after completing their studies. The majority of students—68.4% of women and 65.2% of men—secure their first job in the same region where they studied, and approximately 5% of both men and women move abroad for work.

Since the focus of the paper is on gender norms and women's outcomes, Table A.8 zooms in on women's mobility patterns based on the quartile of FLFP in their province of origin. Both groups have significant migration outside their provinces of origin, with women from more egalitarian regions migrating at a higher rate. Women from less gender-egalitarian areas, however, migrate longer distances, such as outside their home region. Among women who migrate, destination patterns reveal that those from high-FLFP regions tend to relocate to areas with similarly high FLFP, leading to unequal exposure to gender norms. Specifically, women from high-FLFP provinces find themselves in programs where 67% of peers are from above-median FLFP regions, compared to 27% for women from low-FLFP provinces. Differences in field specialization are modest: women from low-FLFP areas tend to select more scientific, engineering, and psychology fields, while women from high-FLFP areas are more likely to pursue humanities, economics, statistics, and architecture. Finally, women from low-FLFP regions display greater likelihood (54.8% vs. 37.8%) of working outside their birth province compared to those from high-FLFP regions, reflecting a lower rate of return migration after completing their studies, as shown in the bottom panel.

Peers' composition. As a consequence of high mobility, Master's programs are heterogeneous in terms of students' geographical origins. Panel (B) of Figure 1 offers a visual snapshot of this "melting pot", mapping each program by the proportion of students from high-FLFP provinces (y-axis) and from below-median FLFP areas (x-axis). Over one-third of programs are populated exclusively by students from below-median FLFP regions. However, many programs show a balanced representation from all quartiles, as represented in the central region. About 5% of programs only have students from above-median FLFP areas. The exact distribution of students' geographical origins across degrees is also presented in Figure A.2, together with the share of students these degrees represent. I will discuss the implications of this specific peer allocation for my findings and potential extrapolations in Section 8.

FIGURE 1. Geographical composition of students within degrees



(A) Mobility

(B) Cultural background

Notes. Panel (A) represents degrees by the % of movers in 2016. One unit corresponds to a degree (N=1,572). The red line corresponds to the median across degrees. In Panel (B), each dot corresponds to a degree program (N=1,572). For each degree, I plot the share of students from provinces in the highest quartile of FLFP (y-axis), alongside the share of students from provinces with FLFP in the first or second quartiles (x-axis). Data refer to 2016.

3.3 Size and Relevance of Peer Groups

The small size of university programs is ideal for studying social interactions. Unlike prior studies that define peer groups broadly as all students within the same school cohort, my focus is on a more precise and potentially more relevant group: students within the same Master's degree cohort. The typical program is small, with a median (mean) size of 34 (47) students, and a range between 4 and 410, as shown in Figure A.3 (Panel A). Gender distribution is also balanced, with few programs showing a strong male or female predominance (Panel B).

One advantage is that small peer groups reduce the likelihood of endogenous sorting into subgroups, a mechanism often present in larger settings (Carrell et al. (2013)), ensuring that students frequently observe and interact with many of their classmates. Moreover, the lenght of exposure—at least two years spent with the same cohort—intensifies these peer interactions. One additional feature is that, due to institutional features[23], 50% of a degree's course content is fixed, and students are free to allocate only about 10% of their total credits, ensuring that they are exposed to the same classmates throughout their studies. Second, small programs' size is key for identification. When programs are small, even minor idiosyncrasies within a cohort can lead to significant shifts in its composition, offering exploitable variation for identification. Conversely, as program sizes increase, the law of large numbers indicates that cohort compositions will tend to be close to the average, reducing residual variation as I verify in Section 5. Other characteristics of degrees are summarized in Table A.9.

Quantity and quality of social interactions. The strenght of social interactions is confirmed through the results of my survey, where I collected information on the network structure and the frequency and quality of interactions. Answers from a sample of students at the University of Bologna are shown in Table A.4 (description of the survey in Section 10). Social ties are strong, with over 70% of students reporting that they spend leisure time with classmates at least once per week. Homophily by geographical background is limited: only 10% of students predominantly socialize with peers from the same province, while 32% engage more with peers from different provinces, and 58% interact equally with both. Career-related discussions are common among classmates, especially among (but not limited to) same-sex peers. Among female students, 80% report discussing career aspirations and opportunities with female classmates (63% with male classmates); for 46% (20%), these discussions occur often or very often.

Takeaways. Three features of this setting make it ideal for studying how peer influence gender norms: (i) significant variation in gender norms across birth provinces, (ii)

[23] Ministerial Decree 270/2004

substantial migration from these provinces to attend university, and (iii) the small size of Master's programs. This setup fosters a geographically diverse composition within each program, allowing students from a wide array of cultural backgrounds to interact closely over the course of two years. Self-collected survey data confirm that discussions about career paths and aspirations occur frequently among classmates.

4 Two Facts About Early-Career Gender Gaps

4.1 Fact 1: the early-career gender earnings gap

Despite women achieving higher levels of human capital, as reflected in their higher GPA and prior academic records, women earn 11% less per month than similar male peers from the same Master's program (Table 2).[24] This gap is both statistically significant and economically meaningful, representing €1,795 net every year, on average. The earnings gap is primarily driven by differences in the intensive margin of labor supply: women are 5 percentage points less likely to be employed in full-time jobs and work 8.3% fewer hours per week compared to male students of similar academic performance.[25] Thus, about one third of the unconditional gap in full-time employment (shown in Table A.2) originates between students attending the same program. These differences in labor supply cannot be attributed to geographic mobility and persist even when controlling for occupation and industry FEs (Table A.11). The residual gap in hourly wages is much smaller at 2.9%.

Furthermore, gender gaps are pervasive across all programs and fields. This is illustrated in Figure 2, which plots binned degree-specific effects on monthly earnings and full-time employment for women against the corresponding effects for men. OLS estimates of the slope are presented, after re-weighting each degree for the share of students it represents across all years. Although there is a strong correlation between the average premiums for male and female students within each degree, women across all degrees are systematically employed in jobs with lower earnings (Panel A) and fewer weekly hours (Panel B). Moreover, these gaps remain stable and do not shrink within the first five years of entering the labor market.

[24] This is consistent with estimates by Bovini et al. (2023), who use individual-level administrative data for all university graduates in Italy, linking education records from the Ministry of Education with social security data from 2011 to 2018.

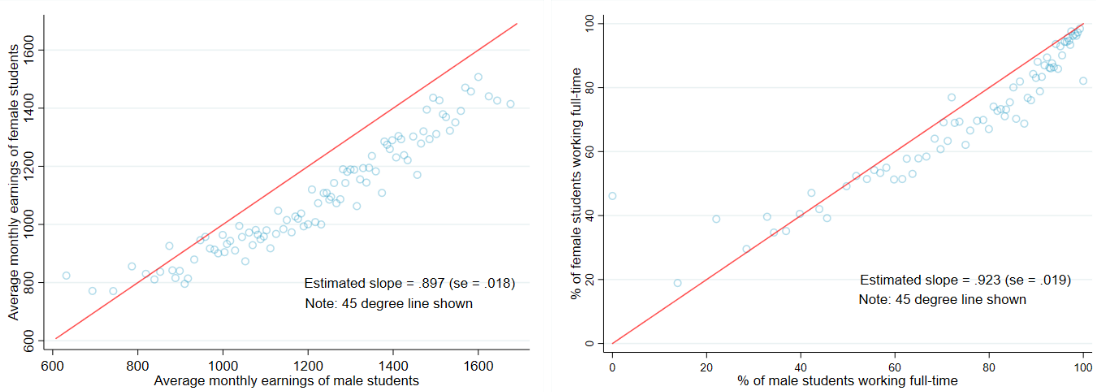
[25] No differences are instead observed on the extensive margin of labor supply (Table A.10).

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 dummy, after including degree and cohort fixed effects and controlling for GPA. In Column (1), the outcome variable is net monthly earnings. In Column (3), the dependent variable is an indicator for holding a full-time contract (typically 40 hours per week). The sample consists of female and male students who are employed one year post graduation. Standard errors are clustered at the degree level.

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.

Overall, these descriptive facts provide comprehensive evidence of systematic gender differences in earnings and labor supply at the start of the career among highly skilled individuals in Italy. Previous research on gender gaps at labor market entry among highly skilled individuals had mainly focused on the U.S. and narrower groups (such as graduates from elite universities or specific fields). These studies found little or no gender differences in working hours at labor market entry (Cortes et al. (2023)) and documented that such differences typically become significant a few years after entering the labor market (Bertrand et al. (2010), Azmat and Ferrer (2017)).

Fertility and couple decisions. While the focus of a prominent body of literature has been on the gendered effects of parenthood in driving gender differences in labor supply[26], realized fertility is not a major factor in this setting. In the sample, the average age of women is 24, with only a small fraction having children or being married/cohabiting (3.7% and 16.1%, respectively). Estimates of the gender earnings gap are robust to the exclusion of these two groups (Table A.12). Moreover, analysis of expectations data from my survey suggests that anticipated fertility is unlikely to be a major factor in women's overrepresentation in part-time jobs. On average, women in this sample expect to have their first child at age 31—well after entering the labor market—and only a minority anticipate working part-time or exiting the workforce due to motherhood. A more comprehensive examination of this potential channel will be provided in Section 10.

Timing of job acceptances. Previous research has emphasized the role of gender differences in job search behavior, such as women accepting job offers earlier due to higher risk aversion, as a driver of early-career earnings disparities (Cortes et al. (2023)). This explanation is, however, not supported by these data. In this study, both women and men start their job search at similar times, yet women actually accept job offers later than their male counterparts (Table A.2). Furthermore, the gender earnings gap does not appear to shrink over the course of the job search period (Figure A.5).

4.2 Fact 2: Cultural Persistence

Women's labor supply decisions are shaped by the societal role models to which they were exposed during childhood—specifically, the working behavior of other women

[26] Examples include: 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. (Forthcoming))

in their birth province—a phenomenon I refer to as *cultural persistence*. Following the epidemiological approach of Fernandez (2007), to isolate the influence of culture from that of markets and institutions, I examine the working behavior of female *movers* using information on their province of residence prior to entrance in college and their province of work. I define *movers* as individuals working in a province different from their birthplace.[27]

The role of early cultural exposure assessed by analyzing the relationship between the labor supply of female movers and various measures of gender culture in their birthplace (defined in Subsection 3.1). The fundamental idea underlying this approach is that movers to the same local labor market share the same market conditions and institutional settings, but they may not necessarily share the same beliefs or preferences. Conceptually, if women form beliefs by observing the working behavior of older women, as suggested in the seminal studies of Fernandez (2013) and Fogli and Veldkamp (2011), we would expect differences in labor supply based on the FLFP in their province of origin. I test this in Table 3, which compares the labor supply of female movers depending on the quartile of FLFP in their province of origin, following the specification:

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

where i refers to a female graduate in the subsample of movers, who has completed a Master's degree d in a given cohort c and is employed in province p. Q4FLFP is an indicator variable that equals 1 if a graduate was born in a province with FLFP in the top quartile, and 0 if from the lowest quartile.[28] θ_d, α_c, γ_p are a set of degree (master x university), cohort and province of employment fixed effects. In some specifications, I add to the baseline model a set of covariates (GPA and fixed effects for parents' occupations).

The results indicate that female movers originating from high-FLFP provinces have significantly higher labor supply compared to those from low-FLFP provinces, even when they work in the same local labor market and graduate from the same Master's program. This difference is statistically significant and substantial, translating to a 7.6%

[27] This approach has been recently used by Kleven (2024), Charles et al. (2024) and Boelman et al. (Forthcoming).

[28] For simplicity I only focus on the two most extreme quartiles (where the average FLFP rates are 34% and 62%), though labor supply differences are also observed between intermediate quartiles, particularly between the first and second.

increase in weekly hours worked and a 2.2 percentage point higher likelihood of full-time employment (Columns 2 and 5). This results in a 6.2% increase in earnings, equivalent to €872 annually. Estimates vary little when accounting for student's performance and parental background. Robustness checks confirm the consistency of these findings across various measures of gender culture at the provincial level, while the effects are notably smaller when non-gender-specific factors are considered.

TABLE 3. Estimates of gender culture on women's labor supply at labor market entry

	(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. 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.

One concern in attributing these differences to gender culture is that movers born in low-FLFP or high-FLFP provinces might differ in other dimensions that impact their outcomes. To investigate the importance of such concerns, Table A.13 contrasts the abilities, educational backgrounds, and socio-economic profiles of female movers from provinces in the top and bottom quartiles of FLFP. Predictions from the empirical model 1 reveal that, overall, female movers from high-FLFP provinces share similar characteristics with their classmates from low-FLFP regions. Notably, parental educational is comparable between the two groups, while some differences emerge in parental occupations: students from low-FLFP areas are less likely to have parents in high-SES jobs and more likely in medium-SES roles. In contrast, an equal share of fathers in both groups hold low-SES jobs. The labor market participation of mothers[29] strongly correlates with local gender culture, although in both groups it is significantly higher than the national average. Importantly, these differences in maternal role models do not mediate the relationship between local gender culture and women's labor supply. Women from low-FLFP areas appear to be more academically selected, with a higher likelihood of having attended academic high-school tracks (*liceo*), especially in science and humanities. In sum, the data does not indicate that these women possess attributes that would account for their poorer labor market outcomes compared to those from high-FLFP regions.

A second concern is that other local factors correlated with FLFP may influence individuals' beliefs and preferences. If these non-gender-specific factors drive the relationship, we would expect similar effects for men. To test this, I conduct the same epidemiological analysis on the sample of male students (Table A.14). The results show no significant differences in full-time employment based on the FLFP of men's province of origin. While there is a modest positive relationship between FLFP and men's working hours—indicating a slightly higher likelihood of overtime in full-time jobs—the coefficients are half the size of those for women, and further diminish when controlling for other local characteristics.[30] This suggests that the observed relationships are primarily driven by gender-specific cultural factors rather than general local influences. Several factors may drive the observed cultural persistence, including variations in preferences, beliefs, access to information, and even employers' biases. I will explore these potential channels in Section 10, presenting evidence of asymmetries in specific beliefs linked to the FLFP of the province of origin.

Takeaways. The earnings and hours worked of female and male graduates differ systematically from the onset of their careers. These large gaps are not driven by fertility or occupational sorting, but are linked to *cultural persistence*. Women's labor supply —unlike men's—is shaped by early exposure to the gender norms in their province of origin.

[29] This refers to the student's response about whether their mother is housewife or participating in the labor market at the time of the survey.

[30] Notably, a stronger relationship emerges between men's working hours and full-time employment when using quartiles of male labor force participation (MLFP).

5 Identification of Peer Effects

How do peers influence the transmission of gender norms? And what impact does exposure to peers from different cultural backgrounds have on women's labor supply decisions? This section outlines the empirical framework used to address these questions.

Identifying peer effects poses significant challenges, particularly due to *selection* or endogenous peer formation. Since students choose the programs and universities they apply to, the peers they encounter are not random. Hence, exposure to certain peer characteristics likely correlates with their own unobserved traits that influence their initial choice of peer group in the first place and potentially affect their labor market outcomes, leading to *correlated effects* in the Manski terminology (Manski (1993)).

To overcome the selection issue, my identification strategy exploits within-degree variation in the geographic origins of peers that consecutive cohorts of students encounter. This approach, first proposed by Hoxby (2000) to study how classmates' characteristics affect educational outcomes, has become widely used for studying peer effects in education.[31] The intuition is that while students select programs based on time-invariant characteristics - e.g. program quality and average peer composition - they cannot precisely control the specific composition of their cohort's peers. Given the wide geographic diversity among applicants, it is unlikely that students can control the exact mix of peers they encounter. In other words, the key assumption is that changes in the geographical origins of students enrolling in a given program across consecutive years are *as good as random*, i.e. no variables simultaneously influence the characteristics of the students and the outcomes of interest. I adopt a multitude of approaches to detect possible violations of this assumption (Subsections 5.2 and 7.1).

In practice, implementing this design also requires longitudinal administrative data that allows tracking how peer composition within Master's programs evolves over time. My dataset is well-suited for this analysis, as it includes a large panel of Master's programs—covering nearly the entire student population in Italy—across multiple enrollment

[31] A non-exhaustive list of studies includes: Angrist and Lang (2004), Lavy and Schlosser (2011), 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), Cools et al. (2022).

cohorts from 2012 to 2016.

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 refers to a student who attended degree d in cohort c. $\overline{FLFP}^{FP}_{-i,dc}$ and $\overline{FLFP}^{MP}_{-i,dc}$ are the sample moments of the leave-one-out distribution of the FLFP in the province of origin of students who belong to a specific gender, degree and cohort:

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

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

Since the leave-one-out strategy introduces a mechanical negative correlation between a student's own FLFP and the average FLFP in the provinces of her 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 main parameters of interest are δ^{FP} and δ^{MP}, i.e. the treatment effects of exposing a student to a set of female or male peers that are coming from places where the FLFP is one percentage point higher. For simplicity, I present the empirical model with FLFP as the measure of gender culture, but I estimate this model with all additional measures outlined in Section 3.

Taking advantage of the panel nature of the data source (repeated observations on Master's programs), the inclusion of degree fixed effects θ_d allows to account for degree characteristics that are constant across cohorts, for example whether the program tends to be attended by students with a specific set of background characteristics. More specifically, it accounts for time-invariant unobserved determinants of earnings of students of a given gender who graduate from a given program. Enrollment cohort fixed effects α_c account for confounding factors affecting the outcomes of all individuals within the same cohort. ε_{idc} is the error term, which is composed of a degree-specific random element and an individual random element. Standard errors are clustered at the degree level to account for potential correlation in students' outcomes within degrees.

The main outcomes of interest are net monthly earnings, weekly hours of work, an indicator variable for full-time employment and hourly wages. Additionally, the empirical model will also be used to assess the effects of peers' characteristics on a number of other job characteristics, such as the type of occupation and industry, location, or contract type. I estimate the model separately on the samples of female and male students.

5.2 VALIDITY OF THE EMPIRICAL STRATEGY

Threat to identification. OLS estimates of δ^{FP} and δ^{MP} are unbiased if $\overline{FLFP}^{FP}_{-i,dc}$ and $\overline{FLFP}^{MP}_{-i,dc}$ are uncorrelated with time-varying unobserved factors influencing students' earnings, conditional on degree and cohort fixed effects. In essence, changes in the composition of students across adjacent cohorts of a program should stem from random fluctuations. This assumption is plausible given the admission rules, where most Master's programs select students based on academic performance (such as entrance exams or undergraduate GPA) and admission is capped. In these programs, variations in $\overline{FLFP}^{FP}_{-i,dc}$ and $\overline{FLFP}^{MP}_{-i,dc}$ reflect shifts in the geographic origins of students whose scores meet admission criteria. This design thus assumes such geographic variations are idiosyncratic, conditional on bachelor's GPA. In contrast, for non-selective programs, year-to-year changes in students' geographic origins stem from shifts in the applicant pool composition.

Violations of the identifying assumption may arise from changes in admission policies that alter student selection, such as adjustments to program size or admission criteria. In the absence of detailed data on these policies, I adopt a data-driven approach to identify potentially non-random changes in size and ability composition, excluding affected programs from the analysis (see Subsection 7.1). Another potential violation occurs if regional labor market trends influence the applicant pool for programs in that region or if shifts in the student composition within a program affect the selection of new students. This section aims to address these concerns and evaluate the validity of this empirical approach.

Balancing tests for cohort composition. A first set of checks consists in verifying that there in no selection, based on observables, into peer groups. I proceed in several steps. First, I conduct a series of balancing tests to assess whether the peer composition within a Master's cohort is systematically related to a large vector of high-quality measures of student characteristics observable in the administrative data and in the institutional survey. For these placebo tests, I select predetermined covariates that cannot be causally influenced by peers but may correlate with unobserved characteristics of students enrolling in the same programs. These include prior academic performance indicators (such as Bachelor's and high school grades) and measures of family socioeconomic status, derived from detailed information on parents' occupations and educational backgrounds. Equation 2 is estimated using these covariates as dependent variables. Tables A.15 and A.16 present OLS estimates of δ^{FP} and δ^{MP} for female and male students, respectively. Each column corresponds to a distinct regression, with a different characteristic as dependent variable. The results indicate that none of the estimated correlations are significantly different from zero, suggesting that exposure to peers from high-FLFP provinces within the Master's program is unrelated to outcomes measured prior to entry in the program.

I employ a second approach to test whether cohorts with varying geographic compositions exhibit student characteristics associated with different labor market outcomes. This involves two steps. First, I run separate regressions for female and male students, predicting their labor market outcomes—such as labor supply at the extensive and intensive margins and earnings—based on their background characteristics, including age, high school type (10 categories), high school and Bachelor's grades, parents' citizenship (Italian vs. non-Italian), and fixed effects for parents' educational qualifications (10 categories) and occupations (12 categories). In a second step, I use these predicted labor market outcomes as dependent variables in equation 2 to check balancedness with respect peers' composition. Table 4 presents these results separately for female and male students. The findings indicate that predicted labor market outcomes are balanced across cohorts, providing strong evidence that cohort-level changes in peer geographic composition are uncorrelated with covariates that explain students' labor market outcomes.

I conduct a third test by regressing the two treatment variables $\overline{FLFP}^{FP}_{-i,dc}$ and $\overline{FLFP}^{MP}_{-i,dc}$ on all observable predetermined covariates, including cohort and degree fixed effects. I then perform Wald tests for the joint significance of all regressors. The resulting p-values are 0.381 and 0.221, respectively, implying I cannot reject the hypothesis that the regressors collectively do not explain the treatment variables.

TABLE 4. Balancedness of Predicted Labor Market Outcomes

Panel A. Female sample

	(1)	(2)	(3)	(4)
	Pr(employed)	Log(monthly earnings)	Log(weekly hours)	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)	(2)	(3)	(4)
	Pr(employed)	Log(monthly earnings)	Log(weekly hours)	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 x university) fixed effects. The estimating equation is 2 in the main text. All regressors are standardised. Standard errors are clustered at degree level. Labor market outcomes are predicted separately for female and male students based on regressions of labor market outcomes on a set of pre-determined invididual covariates: age, type of high-school (10 classes), high-school grade, BSc grade, dummy for mother's/father's citizenship (Italian vs. not), FEs for education titles of mother and father (10 classes), FEs for occupations of mother and father (12 classes).

Overall, these results suggest that the treatment variable is unlikely to correlate with unobserved, time-varying factors affecting labor market outcomes. Building on the framework of Altonji and Blank (1999), we can infer that selection on observed characteristics reasonably proxies for selection on unobservables, supporting the validity of the identification strategy. However, this does not fully rule out the impact of concurrent institutional factors, such as local labor market shifts, that may influence outcomes across student cohorts. I address these potential concerns through a series of robustness checks (Section 7.1), verifying that the results hold when adding degree- or region-specific time trends or when excluding degrees with potentially non-random changes in size or composition.

5.3 Identifying variation

Crucial to this empirical strategy is the presence of sufficient variation in peers' geographic composition across consecutive cohorts within each Master's program. Table 5 provides descriptive statistics for the average FLFP in peers' province of origin across degrees, before and after removing degree and cohort fixed effects. The raw standard deviation of this measure is 8.50 percentage points among female peers and 8.59 percentage points among male peers, and is reduced to 1.86 and 2.13 after netting out degree and cohort fixed effects.[32] Most of the variation in student characteristics occurs across different degrees, indicating that there is sorting of students, as expected. However, there is also some variation—approximately one-fourth to one-fifth of the total variation—within a degree over time. I rely on this residual variation to estimate peer effects, which is sufficient to yield precise estimates. A visual representation of the time-series evolution of FLFP in peers' provinces is presented in Figure A.9 for a randomly picked sample of degrees.

TABLE 5. Raw and Residual Variation of Peers' Gender Culture

	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.

[32] The same descriptive statistics for the other measures of gender culture are shown in A.17.

Importantly, the size of this residual variation aligns with what would be expected if student allocations to cohorts were truly random. To test this, I conducted 500 simulations that randomly assigned students to degrees and cohorts while simulating the distribution of FLFP and program sizes. In these simulations, the residual sd of the average FLFP in peers' provinces centers around 1.95 percentage points, with a range from 1.87 to 2.02 percentage points, which is consistent with or very close to the actual sample values.

Figure A.6 visually represents the residualized FLFP in peers' provinces, with separate panels for female peers (Panel a) and male peers (Panel b).[33] Deviations from the average program composition closely align with a normal distribution, which is plotted for comparison. The shape of the distribution further supports the idea that student's geographical composition is as good as random, conditional on the included controls.

Identifying variation and program's size. If the variations in students' characteristics across cohorts within a degree program were truly random, the law of large numbers would predict that the average characteristics of peers in a cohort would converge to the true average characteristics of the program as the program size increases. This leads to a testable prediction: the magnitude of cross-cohort changes in students' geographical origins within a Master's program should decrease as the program size grows. The empirical test is illustrated in Figure A.7, which plots the residualized female labor force participation (FLFP) in peers' provinces for degrees in the lowest and highest quintiles of size—specifically, degrees with an average size below 22 students and those with sizes ranging from 70 to 410 students. Additionally, Table A.18 provides summary statistics of the FLFP in peers' provinces by program size quintiles. While the raw standard deviation of these variables shows little change across quintiles, the residual variation decreases monotonically as program size increases, consistent with random fluctuations.

Takeaways. Master's degrees are sufficiently small to offer substantial cross-cohort variations in the geographical origins of their students. My empirical strategy leverages this variation, assuming that it is as good as random, to identify the effects of peers' gender norms. Through extensive balancing tests, I show that (i) this variation is uncorrelated with

[33]Figure A.8 provide the same graphical evidence for the other measures of gender culture.

numerous high-quality, predetermined student characteristics, such as prior academic performance and socioeconomic background, and (ii) predicted labor market outcomes are balanced across cohorts. I also demonstrate that this variation is concentrated in smaller programs (which make up the majority of my sample) and decreases monotonically as program size increases, consistent with random fluctuations.

6 Baseline Estimates of Peer Effects

Estimates of peer effects on female earnings and labor supply. Estimates from the empirical model on the sample of female students are presented in Table 6. The outcome variables are net monthly earnings, weekly hours worked and hourly wages, all in logarithmic forms, and an indicator variable of full-time employment (generally 40 hours/week), all measured one year post graduation. Regressors are standardised. Results indicate that women who study in cohorts where female classmates are born in places with higher FLFP increase their labor supply along the intensive margin, both through higher take-up of full-time jobs and increases in weekly hours worked (Columns 2 and 3). The magnitude of this effect is large: 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 and in a 1.9 percentage points increase in the likelihood of full-time employment one year after graduation, a 2.7% increase relative to the mean. This translates into a 3.7% increase in their monthly earnings.[34] These estimated peer effects are economically significant, comparing to 33% – 40% of the size of the gender differences in the same outcomes and accounting for 45% – 76% of the gap between women born in low-FLFP and high-FLFP provinces. Consistent with evidence presented before, there are no effects on the extensive margin of labor supply or on survey response likelihood, minimizing concerns that peer composition might influence the selection of women into the analysis sample (A.20).

These findings underscore the presence of gender-specific peer effects for women. In particular, the positive effects on earnings and hours worked are entirely driven by variations in the gender culture of female peers. By contrast, the estimates of δ^{MP} are consistently zero, indicating that exposure to male classmates from provinces with higher

[34] Results are identifical when controlling for province of origin FEs instead of the FLFP in a student's province of origin (Table A.19).

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.

FLFP does not influence women's earnings or labor supply decisions. There are several reasons why the gender of peers might matter in this context. A key factor lies in the mechanisms driving peer effects. Previously, I documented a much stronger association between women's labor supply and gender norms in their province of origin, while men's outcomes showed weaker or no relationship with these cultural measures. Consequently, increasing the proportion of women from high-FLFP areas within a cohort likely raises the presence of individuals with beliefs and preferences favoring full-time employment—a pattern that is less pronounced among men. Thus, if peer effects operate through (i) conformism or (ii) social learning, it is reasonable to expect limited influence from male peers in this setting. However, opposite-sex peers might still affect women's labor market decisions through other channels, especially where couples are likely to form (Bursztyn et al. (2017)). For example, men from more egalitarian backgrounds may have different expectations of their partners' work behavior, as suggested in Fernández et al. (2004). If students pair with classmates, this could introduce a pathway by which male peers' gender culture might influence women's choices. Yet, this potential explanation is not supported as the share of couples formed within the same program is low, as answers to mu survey reveal (Section 10). A third explanation lies in the structure of social networks. As documented in Section 3, women appear to discuss career opportunities more often with female classmates than with male peers—a pattern widely observed in sociology (McPherson et al. (2001)). Homophily, or the tendency for peer groups to segregate by gender, can significantly shape how information spreads (Currarini et al. (2009)).

Estimates of peer effects on female occupational choices. Table 7 presents estimates of peer effects on the types of occupations and industries women enter one year after graduation. Occupations and industries are categorized based on their average monthly earnings and the share of full-time employment. The dataset includes 20 occupations and 21 industries. An occupation or industry is classified as "high-earnings" or "high-full-time" if it ranks above the median in these distributions. These four indicators are used as outcome variables. The results indicate that exposure to female classmates from high-FLFP areas affects women's occupational choices (Columns 1-2). Specifically, a one standard deviation increase in $\overline{FLFP}^{FP}_{-i,dc}$ is associated with a 1.8 percentage point increase in the likelihood of choosing a high-earnings occupation and a 1.6 percentage point increase in the likelihood of selecting an occupation with a high share of full-time jobs, representing a 4.9% and 3.1% increase relative to the mean, respectively. As highlighted in the previous paragraph, peer effects are gender-specific. To assess the role of occupational changes in the rise of women's labor supply, I re-estimated the model for weekly hours worked, including occupation and industry fixed effects. Although the estimated coefficient for δ_{FP} is reduced by about one-third, the coefficient on weekly hours remains large and statistically significant, suggesting that changes in occupations account for only part of the increase in women's labor supply. This finding aligns with earlier evidence showing that occupational differences between men and women explain less than a third of the total gap in labor supply.

Estimates of peer effects on other job characteristics. While exposure to female peers from high-FLFP provinces affects women's labor supply, earnings, and occupational choices, it does not impact sorting along other observable dimensions, such as employers' characteristics. For example, hourly wages are not affected (Table 6, Column 4), and there

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.

is no significant effect on the industry in which women are employed. Table A.21 presents estimates of the empirical model for other job characteristics observed in the data, such as whether the employer is in the public or private sector or the type of employment contract (permanent, no contract and self-employment). None of these variables show any influence from peer exposure.

Absence of peer effects on male outcomes. Table A.22 presents the analysis for the male sample as a placebo test. If the FLFP in a student's province of origin indeed reflects gender-specific beliefs and preferences, we would not expect peer gender culture to influence men's labor supply or earnings—just as men's own outcomes are little affected by these norms in their origin province. However, indirect effects, such as spillovers, might still arise, for example if some men feel pressure due to women's rising aspirations. The findings confirm that exposure to female or male peers from high-FLFP provinces has no impact on men's weekly hours or likelihood of full-time employment. A small positive effect on men's hourly wages is observed, significant at the 10% level, though this effect disappears once additional local characteristics are included in robustness checks. Due to the lack of influence on men, peers contribute to a reduction in gender gaps in earnings and labor supply by approximately 21-40%.

6.1 Sensitivity to Measures of Gender Culture

In this sub-section, I assess the sensitivity of my estimates to alternative measures of local gender culture. Specifically, I examine whether results vary when using eight alternative proxies for local gender culture, as defined in Section 3. The empirical model is:

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

where Z_{idc} represents a measure of gender culture from the student's own province, and $\overline{Z}^{FP}_{-i,dc}$ and $\overline{Z}^{MP}_{-i,dc}$ capture the average of this measure in the provinces of female and male peers, respectively. The results for log(monthly earnings) are presented in Table A.23. Each column displays estimates from a regression with a different proxy for peers' gender culture, as labeled by each column header. Column (1) serves as a baseline, replicating the results with FLFP. Across the different measures of students' gender culture, the estimates remain consistent, with slightly larger effects observed when gender culture is proxied by labor market behavior of younger women and recent female graduates, suggesting this group may be a more relevant reference. When peer gender culture is defined by female labor market behavior (Columns 1-6), estimated peer effects range from 0.035 to 0.041. Proxies based on firms' gender culture and historical female-to-male literacy rates yield somewhat smaller estimates (0.016 and 0.029, respectively) but remain statistically significant at the 5% and 1% levels.

Takeaways. Exposure to female classmates from provinces with a one standard deviation higher female labor force participation increases women's likelihood of entering full-time employment at the start of their careers, partly due to sorting into occupations with more full-time roles. Because male students are not affected, peers narrow gender gaps in early-career earnings and labor supply by 21-40%. Estimates remain consistent across eight alternative indicators of gender norms in students' provinces.

7 Robustness and Sensitivity

This section has two main objectives: (i) to corroborate the validity of the empirical design, and, once the causal relationship between women's outcomes and peer composition is confirmed, (ii) to determine whether the estimated effects can be specifically attributed to peers' gender norms rather than to other characteristics. To prevent duplication in the presentation of robustness tables, I only focus on the impact of peers on log(monthly earnings) but results are valid for all other outcomes analyzed before.

7.1 Robustness

Consider that the unobserved determinant of students' earnings, ε_{idc}, in equation 2, is composed of a degree-specific random element, ν_{dc}, which reflects time-varying inputs at the degree level, and an individual random element, u_{idc}. Balancing tests in Section 5.2 suggest that changes in $\overline{FLFP}^{FP}_{-i,dc}$ and $\overline{FLFP}^{MP}_{-i,dc}$ are likely uncorrelated with u_{idc}, as these show no association with various observed individual characteristics, such as ability and socio-economic status. This section assesses whether the identifying variation is uncorrelated of ν_{dc}. Changes in the degree-specific component could arise from: (i) shifts in program characteristics, possibly due to admission policies affecting program size or the distribution of students' abilities, and (ii) regional shocks that influence labor market outcomes for all students entering a given local labor market.

Trends. While the main specification conditions on degree and cohort fixed effects, degree-specific or region-specific trends could potentially bias the results. As a further robustness check, I include in the baseline specification degree-specific linear time trends in addition to set of baseline controls. The estimates from this specification, shown in Table A.24, remain large and statistically significant at the 1% level. Similarly, the estimates are stable with the inclusion of region-specific linear time trends, as shown in Table A.25.

Non-random changes in peers' composition. Because I cannot directly observe potential shifts in admission policies, I employ a data-driven approach to flag degrees likely to experience non-random changes in student composition and exclude them from the analysis. To identify degrees with trends in size over time, I estimate a separate regression for each degree, using program size in each cohort as the dependent variable and including a constant and a linear time trend. Degrees are flagged as having a trend in size if the p-value for the time trend variable is ≤ 0.10, which is the case for approximately one-fourth of the degrees. I then re-estimate the baseline model on the subset of degrees that were not flagged. The results, shown in Table A.26, are robust, with all coefficients remaining statistically significant at the 1% or 10% levels and showing higher values.

In a second sensitivity analysis, I assess whether degrees experienced substantial shocks in student characteristics that might indicate shifts in selection. I focus on three degree-cohort characteristics: (i) average student ability (mean Bachelor's grade), (ii) the dispersion of student ability (standard deviation of Bachelor's grades), and (iii) cohort size. To evaluate the magnitude of cross-cohort shocks in these dimensions, I first remove degree and cohort fixed effects and analyze the residuals of characteristics (i)-(iii). For each degree d and characteristic Y among (i)-(iii), I construct the following measure:

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

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} denotes the maximum number of observed cohorts per degree (for 92% of degrees, $T_{max} = 5$). I then standardize Z_d^Y by dividing it by the degree's average characteristic across years, $\frac{1}{T_{max}} \sum_{t=1}^{T_{max}} Y_{dt}$. Using this relative measure, I rank degrees and progressively exclude those with larger shocks. Results from this exercise, shown in Table A.27, indicate that the estimates are robust and statistically significant across samples, with coefficients often larger after excluding high-shock degrees.

7.2 Sensitivity

This sub-section assesses the sensitivity of peer effect estimates to alternative sample restrictions. Specifically, I investigate whether the results vary among samples defined by degree size and the proportion of students who completed their Bachelor's degree at the same university. Results are shown in Table A.28.

Cohort size. First, results indicate that estimates are not driven by noise or possible endogenous peer formation stemming from very small programs, since they remain robust to the exclusion of degrees in the bottom decile of the size distribution. Second, Columns 4 and 5 present estimates separately for students in large and small programs, defined by being respectively above and below the mean size. Findings indicate that the baseline estimates are mostly driven by degrees with sizes below the mean (47 students), while peer effects become significantly smaller and less precisely estimated in larger degrees, consistent with previous evidence that the exploitable residual variation is much smaller. Additionally, in bigger programs, students tend to form distinct social networks, possibly resulting in decreased beneficial social interactions among out-group members.

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 re-estimate the model after excluding degrees in which the majority of students hold a Bachelor's from the same institution (Column 6). The results remain robust. Additionally, in Column 7, I restrict the sample to degrees in the bottom 25% by proportion of students with a Bachelor's from the same institution. Despite a reduced sample, the estimated effects are larger than the benchmark and remain statistically significant.

Student attendance to classes. As a placebo test, I analyze the subset of students who do not regularly attend classes during their Master's program, identified in the pre-graduation survey as those working full-time throughout their studies. This group, comprising 8.7% of the sample, is expected to have minimal peer interaction, thus limiting potential peer effects. Consistent with expectations, results examining heterogeneity by class attendance show notable heterogeneity: while peer effects are substantial for students with high class attendance, there is no evidence of peer influence among students with limited attendance.

7.3 Which peers' characteristics matter?

The main finding of this paper is that exposure to female classmates from provinces with higher FLFP (or other related measures) positively impacts women's labor market outcomes. This section investigates whether the observed effects are specifically due to peers' gender culture or other factors that correlate with that, both at the individual and geographical level.

Alternative individual peers' characteristics. I expand the baseline specification by adding controls for seven additional peer characteristics. Results, shown in Table A.29, indicate that the baseline estimates are not confounded by other observed peer characteristics, consistent with prior evidence of minor differences between peers from high-FLFP and low-FLFP areas. Importantly, controlling for indicators of peer ability—such as the proportion of peers with above-median Bachelor's grades or from an academic high school track (*liceo*)[35]—does not alter the estimates. Similarly, the estimates remain robust when incorporating measures of peers' socioeconomic background, such as the percentage of peers with working mothers, college-educated parents, or parents in high-SES occupations. This suggests that the observed peer effects cannot be attributed to peers from high-FLFP areas having higher academic ability or coming from higher-status families. Finally, adding controls for program characteristics, such as cohort size and the proportion of female peers, leaves the estimates unchanged, further indicating that variations in peer geographical origins are not associated with other shifts in program composition.

Alternative geographical characteristics. FLFP measures correlate strongly with several other regional characteristics (Table A.5), raising concerns that the baseline estimates might reflect these other local factors rather than gender-specific cultural norms. To address such concerns, I add to the baseline model alternative controls for other provincial peers' characteristics, alongside the FLFP, as outlined in Table A.5. These variables should capture other dimensions in which places differ—such their overall economic conditions—which in turn could also shape individuals' expectations and behavior. Results,

[35]These are high schools that specifically prepare students for university studies, as opposed to technical or vocational schools. Here, attendance at a *liceo* serves as a proxy for school quality.

presented in Table A.30, show that controlling for a set of alternative provincial measures does not compromise the robustness of my main estimates. Importantly, the cross-cohort variations in women's outcomes are not attributable to increases in the proportion of female or male peers from larger urban areas or regions with higher per capita income[36], as the estimates stay consistent and statistically significant at the 5% and 1% levels even with these controls (Columns 1 and 2). This robustness also extends to controlling for levels of economic activity in peers' provinces, as represented by the share of firms with over 50 employees and the share of firms in the service sector (Columns 3 and 4). Additional controls, such as fertility rates and female educational levels in peers' provinces, similarly leave the estimates unchanged (Columns 5-7). Lastly, while adding male labor force participation (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. When FLFP is included, MLFP in peers' provinces shows no significant correlation with women's outcomes. As a further inspection, I perform a set of placebo regressions, replacing the FLFP in peers' provinces with any of these other measures. The results show that women's outcomes, shown in Table A.31, change little in relationship to cross-cohort changes in these measures, as point estimates are generally small and not statistically different from zero.

Takeaways. Section 7.1 presents evidence from a series of robustness checks and sensitivity analyses. First, it demonstrates that the peer effect estimates remain stable when incorporating degree- and region-specific linear time trends, as well as when excluding degrees likely subject to non-random, cross-cohort changes in size or peer ability (measured by the mean and standard deviation of prior grades). Second, it supports the conclusion that the estimated peer effects are specifically attributable to gender culture in the province of origin. This is confirmed by showing that the results cannot be explained by (i) individual characteristics of peers, such as ability and socioeconomic background, or (ii) other non-gender-specific provincial characteristics, including general economic conditions, male labor force participation, fertility rates, or economic activity.

[36]Note that these variables are defined at the municipal level.

8 Asymmetry in Peer Effects

The Linear-in-Means (LiM) model, as presented in equation 2, is the most frequently estimated framework in the peer effects literature. This model posits that a student's outcome is a linear function of the average background characteristics of her peers. However, this approach imposes strict assumptions on the nature of peer effects. Importantly, it constrains the magnitude of peer effects (δ^{FP} and δ^{MP}) to be the same, regardless of where the student falls within the distribution of student background characteristics. Previous evidence suggests that peer effects are often non-linear in various contexts (Boucher et al. (2024)).[37] The accuracy of the LiM model has substantial implications for social welfare. Nonlinearities in peer effects open up the possibility that some students' outcomes could be improved by changing their peer groups, without negatively affecting others. Conversely, if peer effects are strictly linear in means, then regardless of how peers are arranged, society would achieve the same average level of outcomes. In this section, I explore the potential for such nonlinearities in peer effects.

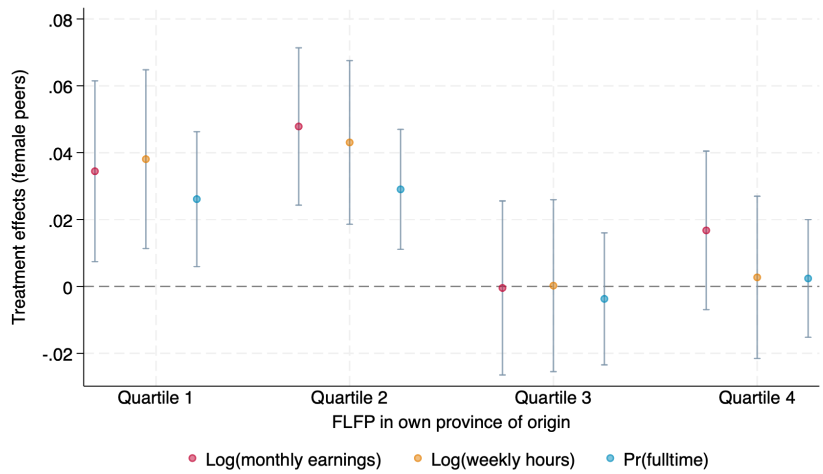
Specifically, I examine specifications that allow the effects of peers to vary with a student's own gender culture. I associate each student with the quartile of FLFP in her province of origin, relative to the distribution of FLFP in the sample. For each degree-cohort, I calculate the fraction of female and male peers from areas with above-median FLFP. I then include interactions between students' own type (first, second, third, and fourth quartile of FLFP) and the fraction of female peers from areas with above-median FLFP, while controlling for degree and cohort fixed effects, following this empirical model:

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

Figure 3 shows the effects of increasing the share of female students from above-median FLFP areas on log(monthly earnings), log(weekly hours), and the probability of full-time employment (Pr(fulltime)), based on students' own FLFP quartile. Across all outcomes,

[37] 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).

FIGURE 3. Heterogeneous Effects by Student's Gender Culture



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.

the results reveal a striking asymmetry in peer effects. The magnitude of the estimated effect for students in the bottom first and second quartiles of the FLFP distribution is significantly larger than that estimated for students in the two highest quartiles of FLFP. For example, an increase of 36% (equivalent to one standard deviation, or to 9 female students) in the share of egalitarian female peers increases the likelihood of full-time employment for students in the first and second quartiles by around 3 percentage points. In contrast, this has no significant effect on women in the third or fourth quartiles. These results suggests that students from less egalitarian areas may benefit the most from having peers from above-median areas. Placing these students into peer groups with a higher shares of students from more egalitarian areas may result in increased overall earnings for women. The empirical model in 5 can be used to quantify the size of peer effects relative to the role of childhood exposure. For example, β_4 corresponds to differences in labor market outcomes between female students in Q4 vs. Q1 when the share of female peers from above-median FLFP areas is at its mean. Increasing the share of female peers from above-median FLFP areas one standard deviation away from the mean make the difference in outcomes between Q4 and Q1 equal to $\beta_4 + \gamma_4$. The estimated coefficients for β and γ across all quartiles are presented in 8. While the gap in outcomes between Q2 and Q1 remains unaffected by peer exposure, the differences between women in the lowest quartile and those from above-median FLFP regions narrow significantly. Specifically, peer effects account for a 65% reduction in the gap in hours worked between Q3 and Q1, and a 58% reduction in the gap between Q4 and Q1. Moreover, peer influences eliminate the gap in full-time employment entirely. Comparing these peer effects to estimates of childhood exposure from the epidemiological approach reveals similar magnitudes. These findings suggest that peer influences from college classmates can mitigate a substantial portion of the initial disadvantage faced by women from less egalitarian areas.

TABLE 8. Magnitude of peer effects vs. own gender culture

	(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

This section investigates the mechanisms of peer influence. First, relying on the administrative data and the follow-up survey, I examine channels related to human capital, migration to local labor markets, and referrals to firms. Second, with data from the institutional survey on students' job-search preferences, I assess whether peer exposure shapes women's preferences for job attributes. Finally, using self-collected data, I explore social learning channels, which will be the focus of Section 10.

9.1 What peers don't do

Human capital. Since women from low- and high-FLFP areas do not differ in their academic ability within Master's programs, we would not expect their academic performance to be influenced by variations in the cohort's geographical composition. To confirm this, I replicate the analysis using contemporaneous academic outcomes as dependent variables. Results for women's GPA, final graduation grade, and a delayed graduation indicator (*fuoricorso*), alongside sample averages, are presented in Table A.32 (Panel A). Across these outcomes, the estimated coefficients are small and statistically insignificant, suggesting that human capital is not a mediating factor in enhancing women's labor market outcomes.

Migration to local labor markets. Shifts in the geographical composition of a cohort can expand students' information about opportunities in different labor markets, potentially affecting women's migration choices and, in turn, the quality of their job outcomes. This influence could also stem from friendships formed among classmates. To test this hypothesis, I analyze the impact of peers on women's mobility decisions, using the FLFP in their destination province and indicators of whether the destination differs from their study or birth province. Results from the baseline model, shown in Table A.32 (Panel B), indicate that women's migration decisions remain unaffected by the geographical origins of their peers, suggesting that this channel does not drive the observed improvements in women's outcomes.

Networks. Economically beneficial labor market connections, such as networks to higher-quality firms, could potentially explain the observed earnings gains among female students.[38] Unfortunately, the absence of firm identifiers in the data limits a formal test of this hypothesis. Nonetheless, I provide suggestive evidence that this mechanism is unlikely to be a primary driver of the increase in women's labor supply. Specifically, support for

[38] For the importance of early-career networks in the labor market, see Zimmerman (2019), Kramarz and Skans (2014), Hampole and Wong (2024), Fischer et al. (2023), Einiö (2023)

this channel would arise if cross-cohort changes in the average FLFP of peers' provinces were associated with shifts in the proportions of locals (students born in the university's province) versus movers. If locals possess better connections to regional firms, for instance via family ties, they might share job information or offer referrals to non-locals. To investigate, I augment the baseline model with controls for the proportions of local female and male peers. Results, presented in Table A.33, indicate that the estimates remain stable. Additionally, the slight increase in estimate magnitude is likely due to a modest yet statistically significant negative effect of higher shares of local students on women's earnings and labor supply.

9.2 What Peers Do: Shifts in Preferences and Social Learning

The central intuition behind my results is that female students from various provinces carry distinct norms and expectations about female employment, that they pass on to their peers. Verifying this hypothesis requires data that allow one to observe changes in women's preferences and beliefs in relationship with the social environment. To investigate social learning, I therefore conducted a new data collection to examine changes in relevant beliefs, in combination with comprehensive data on students' job-search preferences from the institutional survey. I will begin by presenting findings on students' self-reported preferences for various job attributes, and in the next section, I will describe my data collection and the main results related to social learning in detail.

Shifts in preferences. This analysis leverages students' self-reported job-search preferences, collected through the institutional survey before graduation (details in Section 2.2). Students are asked to rank the importance of various job attributes on a scale from 1 (low importance) to 5 (high importance). I construct indices to measure preferences for pecuniary aspects of a job (e.g., salary and career progression) and temporal flexibility (e.g., leisure time and flexible hours).[39] Each index is calculated as the unweighted average of the scores assigned to each attribute and is standardized for interpretability. Additionally, I create a binary indicator to identify students who assign high importance (i.e., a value of 5/5) to a job's social utility—a relevant attribute where I observe significant gender

[39] This approach follows similar methodologies used in studies examining gender differences in job-search preferences (Wiswall and Zafar (2018), Mas and Pallais (2017), Eriksson and Kristensen (2014)).

differences, though it has been largely overlooked in prior research. To assess whether these preferences are influenced by the classroom environment, I use these measures as outcome variables in the empirical model. Results, presented in Table A.34, suggest that socialization with peers holding more egalitarian norms leads to shifts in women's valuation of job attributes, specifically decreasing the importance assigned to non-pecuniary factors like temporal flexibility and social utility. A one standard deviation increase in peers' gender culture decreases women's preference for (i) hours flexibility by 2.7% of a standard deviation and (ii) the social utility of a job by 1.2 percentage points (a 3% change relative to the mean).

10 Social learning: Evidence from a new data collection

Studying social learning requires to observe how beliefs evolve in relation to the classroom environment. I therefore designed a novel survey with three main objectives: (1) to explore variations in women's beliefs based on their childhood exposure to gender norms, (2) to assess the influence of these beliefs on job acceptance decisions, and (3) to examine how these beliefs are updated over time.

Childhood exposure to gender norms and women's beliefs. Prior research has consistently documented links between female labor force participation (FLFP), or related measures, in a woman's country of origin or ancestry and her labor supply decisions, underscoring the role of preferences and beliefs in this transmission.[40] However, these studies often remain agnostic about the specific beliefs and mechanisms that drive this persistence. This survey is designed to pinpoint the beliefs mediating these relationships. Conceptually, childhood exposure to gender norms can shape an array of beliefs that could, in turn, matter for women's early-career decisions. These include beliefs about the role of women in society, expectations about the job offer distribution, expectations about employers' discrimination, as well as expectations about fertility and labor supply in motherhood. This survey elicits these various beliefs over time. In this section, I first document marked heterogeneities in some of these beliefs among students from different

[40] See Fernandez and Fogli (2009), Fogli and Veldkamp (2011), Fernandez (2013), Kleven (2024), Ichino et al. (2024), Boelman et al. (Forthcoming).

provinces and illustrate both theoretically and empirically how these differences affect acceptance of part-time positions. I then leverage the longitudinal nature of this data to examine how these beliefs update over time.

10.1 Survey Design and Administration

I conducted the survey among graduate students currently enrolled at the the University of Bologna. This represents the largest university in Italy, contributing to approximately 7% of all graduates. Importantly, it offers a multitude of cultural backgrounds, as it attracts a significant number of students from various provinces and regions across the country (88.8% and 69.6%, respectively).

To construct a sample of analysis, I randomly selected a sample of Master's degree programs and, within each program, I randomly chose one course in the first semester of the first year and one from the first semester of the second year. Students attending these courses have been invited to take part in the survey. The administration was done in person through classroom interventions. Specifically, in agreement with lecturers, I went in person to one class - usually in the first/last 15 minutes - and I encouraged students to voluntarily complete a 10-minute questionnaire on their mobile phones through the SurveyMonkey platform. Before, I took some minutes to provide general information on the study.[41] To incentivize participation, students had the chance to enter three lotteries with gift cards worth €100.[42] The response rate reached 97% among attending students. Around 77% of students attend classes regularly, based on self-reported attendance in the AlmaLaurea questionnaire. Students were not informed in advance about my intervention to ensure that their attendance in class would be orthogonal to the survey administration. These two features attenuate concerns related to selection.

The survey was conducted 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 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

[41] Specifically, I informed students that the questionnaire was about their beliefs and labor market expectations and was needed for a study on students' career decisions after college. To avoid priming, I did not disclose that the study focused on peer influence or its connection to gender inequalities.

[42] The gift cards were generic and could be used across multiple brands or providers, to avoid any potential selection bias from the choice of a specific provider.

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 students with missing information on country or province of origin (5.8%). The resulting sample includes 490 female students, with 319 in the first year and 171 in the second year of their Master's programs.

Table A.35 presents summary statistics for the entire sample and sub-samples categorized by the FLFP in the students' province of origin. This sample differs from the main sample in some important dimensions. First, it over-represents students from high-SES backgrounds, indicated by significantly higher proportion of parents with university degrees, and includes more students from provinces with higher FLFP. Second, these programs feature higher shares of students who migrated from other provinces or regions. Third, the representation of fields of study differs from the main sample: certain fields (engineering, architecture, healthcare, and psychology) are not covered, while humanities are over-represented.

A comparison of women from high- and low-FLFP provinces of origin highlights differences in the role models they encountered within their families. Students from low-FLFP provinces are more likely to have fathers with higher education levels than their mothers, whereas the opposite is true for students from high-FLFP areas. Additionally, mothers in low-FLFP areas are more frequently impacted by significant *child penalties*, such as career interruptions during their children's early years, compared to mothers in high-FLFP areas. Despite these background differences, the two groups are alike in two important respects: their fertility expectations and their post-graduation job search intentions.

10.3 Learning about The Job Offer Distribution

In this sub-section, I investigate the role of asymmetries in beliefs regarding the job offer distribution and the process of learning. The underlying idea is that women from areas with less favorable labor market conditions for women may hold different expectations about job offer arrival rates compared to those from more egalitarian areas. To investigate this, I gather students' expectations regarding key parameters of a job-search model, including the overall job offer arrival rate and the relative arrival rates of part-time versus full-time job offers. Elicitation of beliefs is done through hypothetical scenarios that aim at reproducing a realistic setting of job search:

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? (α) 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 propose a part-time contract (less than 28 hours/week)? (γ) - 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 will 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)

By fixing the number of applications to ten for all students, the elicitation of arrival rates focuses on capturing beliefs about the likelihood of receiving job offers, isolating this from any variation in expected job-search effort. Additionally, specifying that these applications align with each student's major specialization restricts the set of potential occupations, enabling more precise comparisons of beliefs among students within the same Master's program. Note that, similar to Wiswall and Zafar (2021), students' intentions to accept a part-time job offer are elicited using a stated probabilities approach rather than a discrete choice approach. This method accounts for students' uncertainty when reporting their choices in the survey. A discrete choice model is, in fact, a special case of the stated probabilities approach, representing a scenario where there is no resolvable uncertainty. In this case, individuals would assign a probability of exactly 1 or 0 to the decision of accepting a part-time job. However, the data clearly reject this: only 4.83% of reported probabilities are 1, and less than 1% of probabilities are 0.

Place of birth and asymmetries in beliefs. The analysis of these beliefs is presented in Table 9. To explore potential asymmetries based on childhood exposure to gender norms, Panel (a) focuses on baseline beliefs collected during the students' first year, aiming to capture the student's initial perceptions before any influence from peers. Specifically, the table shows predictions from a linear regression model where each dependent variable—listed in the rows—is regressed on an indicator denoting whether a woman originates from a province with below-median or above-median FLFP, controlling for field fixed effects. The table provides the predicted values with their standard errors, as well as the p-values testing the significance of the differences between the two groups. The results indicate that women tend to have different expectations of these parameters depending on the FLFP in their province of origin. First, women from low-FLFP areas expect a slightly lower arrival rate of job offers (α), though this difference is negligible and not statistically significant—out of ten applications, they expect to receive, on average, 3.21 offers compared to 3.52 for women from high-FLFP provinces. More notably, there is a substantial gap in their expectations regarding the proportion of part-time job offers. Women from low-FLFP areas expect a 6.45 percentage point higher likelihood of receiving a part-time versus full-time job offer, which represents a significant 12.6% increase compared to their high-FLFP counterparts. Additionally, these women are 7 percentage points more likely to indicate they would accept a part-time offer, marking a 12% increase relative to peers from high-FLFP provinces. Importantly, these differences cannot be attributed to differences in observed characteristics between the two groups, as they are unchanged after controlling for students' background characteristics (age, family background), job search intentions, and expected job location, as shown in Table A.36. Furthermore, controlling for major FEs minimizes concerns that these differences are driven my markedly different occupational choices.

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. 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 (319), and in Panel (b), it includes all second-year female Master's students (164). Between 60% and 65% of the students are from provinces with above-median FLFP.

Beliefs updating. Panel (b) of Table 9 investigates how these believes evolve over time, by focusing on answers from students in the second year. Overall, we observe convergence in these beliefs between the two groups, consistent with learning. More precisely, the results show that students significantly update their beliefs about the likelihood of receiving a part-time job offer, in a way that the gap originally observed between the two groups has narrowed considerably (by more than 70%). An analysis of the variance in beliefs within fields further supports evidence of learning. On average across degrees, the standard deviation of students' baseline beliefs γ in the first year is 24.28, which decreases by more than a third in the second year—a statistically significant reduction at the 1% level. What is particularly interesting is the asymmetry in this learning process. Women born in low-FLFP provinces experience strong beliefs' updating and revise their beliefs downwards regarding the probability of receiving a part-time offer relative to a full-time one by more than 5 percentage points (a 9% decrease), converging to the values expressed by their peers from high-FLFP areas who experience only little updating. Why do the two groups update their beliefs differently? One possible explanation is the initial asymmetry in the information available to them. Women from low-FLFP areas might have started with more biased beliefs about job offer arrival rates in their destination labor markets, leading to a more significant adjustment over time. This is a plausible channel, as women from low-FLFP areas are typically exposed to labor markets that differ substantially, in terms of women's outcomes, than those in their home regions, as reflected in their intentions to work predominantly in the North of Italy (Table A.35). These results provide evidence of asymmetric belief updating, which is consistent with the asymmetry in the estimated peer effects. While I cannot precisely quantify the contribution of peers versus other social influences in the process of belief updating, the results strongly support social learning as a mechanism driving peer influence in this context.

10.4 Beliefs and Job Search: an Illustrative Model

To study the relation between beliefs and job search, I propose a McCall type model (McCall (1970)) where risk-neutral female graduates search for their first post-graduation job. For the time being, I abstract from students' gender norms when I lay out the model, and I later introduce parameter heterogeneity when I discuss the model's prediction for differences in part-time acceptances between women from high- and low-FLFP areas.

10.5 Model Setup

My modeling framework is based on a standard model of labor market search à la McCall, augmented to allow for heterogeneous worker beliefs.
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. For simplicity, consider that part-time (P) and full-time jobs (F) are characterized by a fixed number of weekly hours. I express the per-period number of hours in a part-time job as $h^P = \theta h^F$, with $\theta < 1$. The model makes a number of key assumptions. Time t is discrete. All individuals discount the future at rate $\beta \in (0, 1)$. Students are risk-neutral: they have preferences over consumption represented by the instantaneous utility function u(c) = y, i.e. they maximize expected lifetime labor income. As is typical in job-search models, this model abstracts from other

sources of income, so that instantaneous income is given by the following specification:

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

b represents any income associated with not working, such as the pecuniary value of leisure and public unemployment insurance (UI) benefits. y_P and y_F are total per period income associated with either a part-time or a full-time job. For simplicity, I fix the number of hours in a full-time job to unity, so that $y_F = w$ and $y_P = \theta w$.

Unemployed jobseekers search for jobs and, in each period, job offers arrive with probability α^*. A share γ^* of job offers are part-time. A job offer is a random draw from a wage distribution F(w), which has support and non-zero density on $[w_{\min}, \bar{w}]$. Note that, for simplicity, I assume that the wage distribution is the same for part-time and full-time jobs. In each period, if an unemployed worker receives a job offer, she decides whether to accept the offer and leave unemployment or remain unemployed and enjoy the value of leisure b. I do not allow for on-the-job search or job destruction, meaning that employment - both part-time and full-time - is an absorbing state. 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, I use * to indicate "true" or "actual" probabilities of receiving job offers, to distinguish these from the workers' beliefs.

10.6 Workers' Beliefs

I start with the notion that workers make decisions with possibly limited knowledge about job offer arrival rates. Specifically, I assume that workers do not necessarily know the per-period probability of receiving a job offer α^* and the relative share of part-time job offers γ^*. Define α_t and γ_t as the worker's current beliefs about α^* and γ^*. I refer to biased beliefs 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.

10.7 Perceived Values of Employment and Unemployment

I characterize the perceived flow values of unemployment and employment.[43] For a worker with beliefs α and γ, the perceived value of unemployment equals

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

where b is the flow value of unemployment, and α and γ are the worker's beliefs regarding the per-period probability of receiving a job offer and the relative share of part-time job offers. The values of part-time and full-time employment at wage w are respectively

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

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

Note that here, absent job destruction and on-the-job search, it is assumed that, once a worker has accepted a job offer, she remains at her current job at all future periods.

10.8 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 are accepted. The job seeker determines their 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 between accepting a job

[43] I refer to them as perceived as they are based on workers' beliefs about the arrival rates of part-time and full-time job offers instead of the actual ones.

and remaining unemployed. The resulting expression for the reservation earnings equals

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

Note that, 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 job offering wages above these values is accepted. Note that reservation wages are determined based on workers' beliefs. In the following propositions, I outline how biases in beliefs regarding α^* and γ^* theoretically impact reservation wages.

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 Section A.

10.9 Heterogeneous Beliefs and Model's Predictions

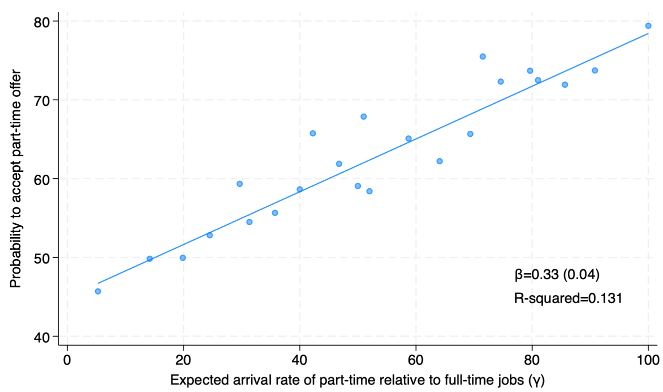
I now introduce heterogeneity in workers' beliefs into the model, considering that workers hold beliefs α_i and γ_i about the arrival rates of job offers, where $i \in (L,H)$. However, throughout the model, I assume that all workers actually face the same true arrival rates, denoted as (α^*,γ^*). I define the beliefs of women from low-FLFP and high-FLFP provinces as (α_L, γ_L) and (α_H, γ_H), respectively. Drawing on the empirical analysis of students' beliefs from the previous section, I assume:

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

i.e. women from low-FLFP areas expect a lower probability of receiving any job offer and a higher likelihood of receiving a part-time offer relative to a full-time one.

A direct corollary of Propositions 1 and 2 is that, all else equal, if women from low-FLFP provinces hold more pessimistic beliefs about the arrival rates of job offers and the likelihood of receiving part-time versus full-time offers compared to women from high-FLFP areas, they will have lower reservation earnings. Consequently, they will have a higher likelihood of accepting a part-time job offer. I test this prediction using data on students' expectations about job offer arrival rates and their intentions to accept a part-time offer, elicited on a probabilistic scale through a realistic hypothetical scenario. These intentions are indicative of how students might behave when faced with part-time job offers during their actual job search. Figure 4 illustrates the relationship between these beliefs and students' job search behavior, showing a strong correlation between their expectations of part-time versus full-time job offers and the likelihood of accepting a part-time offer.

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.

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, representing more than a third of the standard deviation in the sample. These beliefs alone explain 13% of the variation in students' acceptances of part-time jobs in the sample. Estimates are robust to the inclusion of field (or degree) fixed effects (β = 0.27). Table A.37

shows the estimated coefficients from a regression of students' part-time job acceptances on their beliefs about γ (Columns 1-2) and α (Columns 3-4), both with and without controls for field fixed effects. These results additionally show a negative relationship between expected job offer arrival rates and the likelihood of accepting a part-time offer, consistent with the model's predictions[44].

10.10 Expectations of Fertility and Future Child Penalties

This sub-section explores how local gender culture shapes expectations about fertility and anticipated child penalties. Previous studies, such as Boelman et al. (Forthcoming) and Kleven (2024), have shown that the gender norms women are exposed to during childhood have long-lasting effects on their labor supply decisions after becoming mothers. Even in the Italian context, the magnitude of child penalties varies significantly across geographical areas (Casarico and Lattanzio (2023)). If women accurately anticipate these differences in future behavior, their expectations about fertility and future labor supply may vary based on the gender norms they were exposed to when growing up. For instance, women from less egalitarian backgrounds might expect higher employment costs associated with motherhood. As implied by a dynamic labor supply model in the vein of Adda et al. (2017), these differences in expectations likely influence women's career choices even before they have children, particularly in selecting jobs or occupations with different opportunity costs of child-rearing. Whether women anticipate these differences in behavior is an empirical question, that I examine in this sub-section. To achieve this goal, I gathered data on women's expectations regarding fertility and future labor supply.

The analysis of their baseline and updated expectations is presented in Table A.38. At the start of the first year, there are no differences in fertility expectations that can explain the observed labor supply disparities between women from high and low-FLFP provinces. In fact, women from low-FLFP provinces are less likely to expect to have children and anticipate having their first child at a later age compared to their high-FLFP peers. Crucially, when considering future labor supply, those from low-FLFP areas are less likely to foresee reductions in working hours due to motherhood as they are more likely to expect to continue working full-time during the early years of parenthood. This

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

pattern holds across both their unconditional expectations (elicited under scenario 1) and their expectations when full-day childcare is available near their residence (elicited under scenario 2). Additionally, both groups of women anticipate that childcare availability will impact their future labor supply, as the share expecting to work full-time increases by 43%-58%, depending on the group, when access to full-day childcare is available.

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

One year later, both groups have revised their expectations upwards, particularly when full-day childcare is available. Around 80% of women in the two groups expect to work full-time in the early years of motherhood. Contrary to expectations, these results show that women from less egalitarian backgrounds do not anticipate higher employment costs of motherhood when entering the labor market, compared to women from high-FLFP areas. One plausible explanation is that young women may underestimate the career costs of motherhood— a phenomenon particularly pronounced among the college-educated (Kuziemko et al. (2018)). Other sets of explanations relate to intergenerational shifts in the magnitude of child penalties or positive selection bias in the sample of women from low-FLFP areas. Importantly, unlike the asymmetric updating of beliefs regarding job offers, these results indicate that preferences and beliefs about maternal employment evolve symmetrically across both groups.

Takeaways. I identify two primary channels through which peer effects operate. The first channel involves shifts in preferences: exposure to more egalitarian female peers encourages women to place less value on non-monetary job attributes, especially flexibility in work hours. I identify two primary channels through which peer effects operate. The first channel involves shifts in preferences: exposure to more egalitarian female peers encourages women to place less value on non-monetary job attributes, especially flexibility in work hours. The second channel is social learning. Using a unique dataset, I show that there are notable asymmetries in women's expectations of receiving full-time job offers based on their childhood exposure to female role models. These differences account for a substantial portion of the gap in part-time job acceptance rates between women from areas with low versus high female labor force participation. Leveraging data on beliefs over time, I show that women from low-FLFP areas learn about the job offer distribution, considerablly narrowing the gap with high-FLFP peers.

11 Conclusions

Gender norms are by now recognized as fundamental drivers of persistent labor market disparities, over and above traditional economic factors such as human capital accumulation, comparative advantage and discrimination. While most of the literature has been devoted to empirically documenting their long-term persistence, much less attention has been paid to understanding their evolution. A primary challenge in studying the mechanisms of cultural change lies in the need for extensive, multi-source data, as well as settings that allow for exogenous exposure to gender norms.

This paper addresses this gap by providing the first large-scale evidence on the role of college classmates in the transmission of gender norms. To achieve this goal, I exploit quasi-random variation in exposure to peers from areas with more egalitarian gender culture during graduate studies, using a rich combination of data sources. These include administrative and survey data on nearly the entire population of university students in Italy, which link academic records to early-career outcomes and to job-search preferences from a compulsory survey. I also collect novel data that track changes in students' beliefs over time and capture aspects of network structure that are otherwise hard to observe.

I show that the exposure to higher shares of female classmates born in provinces with higher female labor force participation (FLFP) raises the chances that women enter full-time employment upon graduation. Around one third of this labor supply increase stems from increased sorting into occupations characterized by larger shares of full-time jobs. Estimates hold across a wide range of indicators of local gender culture in peers' provinces, and are not confounded by other provincial characteristics, such as economic activity and male labor force participation. Since male students are not affected by the geographical mix of their cohort, a one standard deviation increase in peers' gender culture reduces early-career gender gaps by 21-40%.

A central finding is the pronounced asymmetry in peer effects: exposure to more egalitarian gender norms significantly increases the labor supply of women from below-median FLFP areas but has no effect on women from above-median FLFP areas. This asymmetry means that peer influence can offset a substantial portion of the initial disadvantages faced by women from less egalitarian regions. These findings carry important policy implications, suggesting that educational policies promoting diversity could help counteract persistent gender norms and promote gender equality in the labor market.

By leveraging innovative data sources, I advance our understanding of the mechanisms of cultural transmission. First, I show that women's valuation of non-pecuniary attributes, particularly hours flexibility, decreases in response to peer composition, indicating that preferences adapt to the social environment. A second, more policy-relevant, channel is learning from peers. This follows from a striking asymmetry that I document: women from low-FLFP areas are systematically more pessimistic about receiving full-time offers compared to those from high-FLFP areas, which leads them to accept more part-time jobs. However, my findings show that these belief asymmetries decrease significantly within the first year, driven by strong belief updating among women from low-FLFP areas. These results underscore the importance of information frictions in perpetuating gender norms, a novel angle in understanding gender disparities. This finding suggests that providing accurate information could effectively alter gender norms and reduce labor market disparities.

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Appendix

Appendix A. Appendix: 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

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

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:

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

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

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

Rearranging, I get to the following expression

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

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

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

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:

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

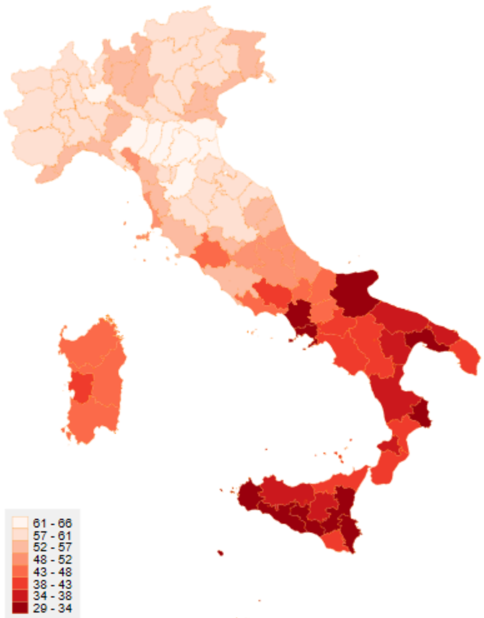
that I rewrite as

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

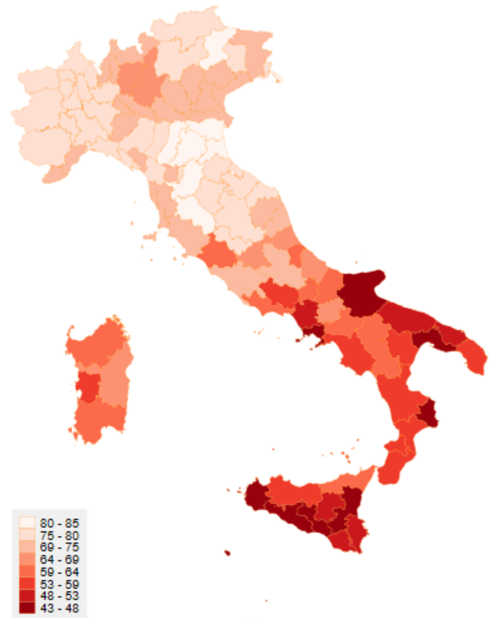
where λ_i represents the per-period probability of exiting unemployment. This probability depends on the true arrival rates of job offers, α^* and γ^*, as well as on women's beliefs about these parameters through their reservation earnings, $R_i(\alpha_i, \gamma_i)$, which are indexed by i to reflect 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, which includes endogenous job search effort (available in the appendix), can rationalize the dynamics of job-search behavior observed in the data.

Appendix B. Additional Figures and Tables

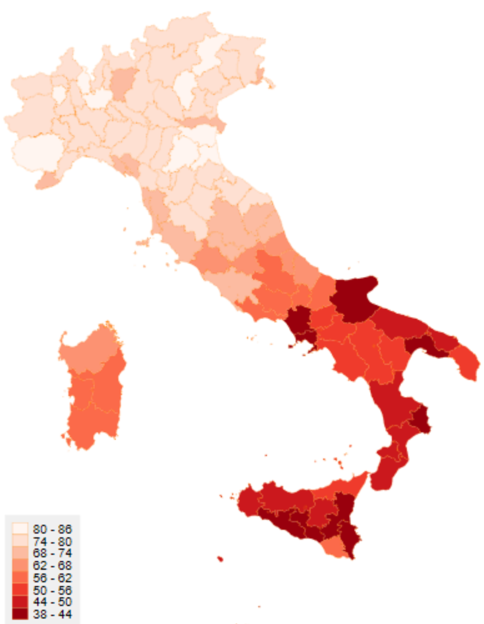
FIGURE A.1. Heatmaps of FLFP and other measures of gender culture



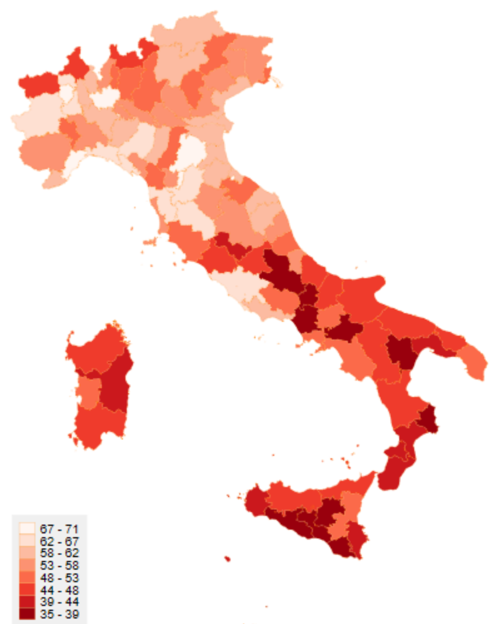
(a) FLFP (%) - Age: 15-64



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



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



(d) % of firms without preference for male workers

Notes. Panel (a) and (b) present the FLFP and the FLFP/MLFP of all women (15-64), and Panel (c) presents the FLFP of young women (25-34) in Italy. These are constructed as averages from 2004-2007. Panel (d) presents the % of firms without hiring preferences for male workers in 2003. All of these measured are defined at the province level.

TABLE A.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	182792	24.5	4.1	133678	0.00
GPA during Master	27.8	1.5	182792	27.4	1.7	133678	0.00
Final grade during Master	108.6	5.6	182792	107.4	6.3	133678	0.00
Time to completion of Master (years)	2.5	0.6	182792	2.6	0.6	133678	0.00
Bachelor grade	101.3	7.4	162091	99.1	8.2	116258	0.00
High school: academic track (%)	84.2	36.5	182477	71.4	45.2	133378	0.00
science (%)	40.3	49.0	182477	56.7	49.5	133378	0.00
humanities (%)	21.2	40.9	182477	10.4	30.6	133378	0.00
foreign language (%)	10.5	30.7	182477	1.9	13.8	133378	0.00
social sciences (%)	10.3	30.4	182477	1.4	11.6	133378	0.00
arts (%)	1.9	13.7	182477	1.0	9.8	133378	0.00
High school: technical track (%)	12.9	33.5	182477	25.1	43.3	133378	0.00
High school: vocational track (%)	1.2	10.9	182477	1.7	12.9	133378	0.00
International high-school (%)	1.7	12.9	182477	1.8	13.3	133378	0.02
High school grade	83.6	11.6	178593	80.8	12.1	130134	0.00
Field of study							
Science, chemistry, biology (%)	13.3	34.0	182792	13.1	33.7	133678	0.06
Engineering (%)	8.2	27.5	182792	27.0	44.4	133678	0.00
Humanities (%)	24.7	43.1	182792	10.4	30.5	133678	0.00
Political and social sciences (%)	11.6	32.0	182792	7.9	26.9	133678	0.00
Economics and statistics (%)	18.5	38.9	182792	24.3	42.9	133678	0.00
Psychology (%)	11.7	32.1	182792	3.1	17.4	133678	0.00
Healthcare (%)	4.0	19.7	182792	2.1	14.4	133678	0.00
Architecture (%)	3.9	19.5	182792	4.9	21.6	133678	0.00
Agriculture (%)	1.9	13.8	182792	2.9	16.9	133678	0.00
Family background							
Matched to administrative records	91.7	27.6	182792	89.6	30.6	133678	0.00
Mother: university education (%)	18.9	39.2	167637	22.0	41.4	119745	0.00
Father: university education (%)	20.0	40.0	167637	24.0	42.7	119745	0.00
Mother: high-school education (%)	50.3	50.0	167637	50.9	50.0	119745	0.00
Father: high-school education (%)	46.0	49.8	167637	47.2	49.9	119745	0.00
Mother is in labor force (%)	71.0	45.4	163753	73.2	44.3	116921	0.00
Father is in labor force (%)	99.3	8.0	162735	99.4	7.5	117051	0.00
Mother: low SES (%)	59.5	49.1	163753	55.8	49.7	116921	0.00
Mother: medium SES (%)	30.2	45.9	163753	32.6	46.9	116921	0.00
Mother: high SES (%)	10.4	30.5	163753	11.6	32.0	116921	0.00
Father: low SES (%)	45.6	49.8	162735	40.5	49.1	117051	0.00
Father: medium SES (%)	23.1	42.1	162735	24.2	42.8	117051	0.00
Father: high SES (%)	31.3	46.4	162735	35.3	47.8	117051	0.00

Notes. The table compares mean characteristics between female and male students in the sample. Variables in this panel were collected in the administrative data and in the institutional survey (data available for 91% of students). SES is categorized based on parents' occupations (12 classes).

TABLE A.2. Summary Statistics of Early-Career Outcomes and the Job-Search Process

	Female			Male			
	Mean	SD	Obs	Mean	SD	Obs	P-value
Respond to follow-up survey (%)	73.7	44.0	182792	73.2	44.3	133678	0.00
Married/cohabiting with partner (%)	16.1	36.8	134506	9.5	29.3	97709	0.00
Has children (%)	3.7	18.8	134514	2.2	14.6	97724	0.00
Currently employed (%)	53.9	49.8	134681	61.8	48.6	97823	0.00
Not currently employed, but has been (%)	15.1	35.8	134681	11.2	31.6	97823	0.00
Never employed (%)	31.0	46.3	134681	27.0	44.4	97823	0.00
Not currently employed:							
Further education (PhD, MBAs, etc) %	12.1	32.6	134479	12.5	33.1	97663	0.00
Internship/training (%)	12.7	33.3	134479	9.5	29.3	97663	0.00
Unemployed searching for a job (%)	16.0	36.7	134674	12.1	32.7	97818	0.00
Out of labor force (%)	5.2	22.3	134674	4.0	19.7	97818	0.00
Currently employed:							
Net monthly earnings (€)	1077.8	499.3	69659	1324.5	509.6	57494	0.00
Weekly hours worked	32.9	13.2	69659	38.6	10.9	57494	0.00
Full-time job (%)	69.3	46.1	69659	86.2	34.5	57494	0.00
Hourly wage	8.9	6.4	69659	8.9	5.7	57494	0.67
High earnings occupation (%)	36.7	48.2	68231	61.5	48.7	56680	0.00
High full-time occupation (%)	51.3	50.0	68231	74.5	43.6	56680	0.00
High earnings industry (%)	34.3	47.5	68434	48.2	50.0	56835	0.00
High full-time industry (%)	38.1	48.6	68434	62.0	48.5	56835	0.00
Permanent contract (%)	23.0	42.1	69431	29.4	45.6	57342	0.00
Fixed-term contract (%)	54.2	49.8	69431	52.2	50.0	57342	0.00
Self-employment (%)	16.1	36.8	69431	15.4	36.1	57342	0.04
No contract (%)	6.7	25.0	69431	3.0	17.1	57342	0.00
Private sector (%)	76.7	42.3	69570	86.1	34.6	57450	0.00
Public sector (%)	16.5	37.1	69570	11.1	31.4	57450	0.00
No profit (%)	6.9	25.3	69570	2.8	16.5	57450	0.00
Use skills acquired during Master (%)	41.8	49.3	69598	47.3	49.9	57457	0.00
Job satisfaction (scale 0-10)	7.2	2.0	69580	7.4	1.7	57453	0.00
Job-search process							
Job search: months from grad.	0.7	1.8	68654	0.6	1.5	56382	0.00
Accept offer: months from grad.	3.0	3.5	69380	2.7	3.3	57356	0.00
Numbers of jobs from grad.	1.3	0.6	69594	1.2	0.6	57454	0.00
Current job: first job after grad. (%)	80.3	39.8	69594	81.0	39.2	57454	0.00
On-the job search | part-time today (%)	58.0	49.4	21390	55.9	49.7	7918	0.00
On-the job search | full-time today (%)	30.8	46.2	48262	28.8	45.3	49573	0.00
Received job offer | part-time today (%)	19.1	39.3	21392	19.4	39.5	7918	0.00
Received job offer | full-time today (%)	21.5	41.1	48267	26.5	44.1	49576	0.00
Received job offer | unemployed today (%)	19.3	39.5	21589	22.1	41.5	11870	0.00
Nb. of job-search channels	3.4	1.8	70887	3.5	1.9	49709	0.00
Prefer full-time to part-time job (%)	93.6	24.5	165921	96.1	19.4	118499	0.00
Available to accept part-time job (%)	82.4	38.1	163200	61.6	48.6	116434	0.00

Notes. The table compares mean characteristics between female and male students in the sample. Variables in this panel were collected in the follow-up survey conducted one year after graduation.

TABLE A.3. Summary statistics of measures of gender culture in the sample, by 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 measures of gender culture 1-6 presented in Section 3, by gender. The sample of female and male students include, respectively, 182,792 and 133,678 students. Students are assigned to provinces based on their residence province prior to enrollment in the Master.

TABLE A.4. Summary statistics of 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 other geographical characteristics in the sample. The unit of observation is a student. Students are assigned to provinces/municipalities based on their residence prior to enrollment in the Master. All measures are defined at the province level when otherwise specified.

TABLE A.5. Pairwise correlations of measures of gender culture and other geoegraphical 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 A.6. Mobility to universities by gender in the sample

	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
Gender culture in province of university					
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

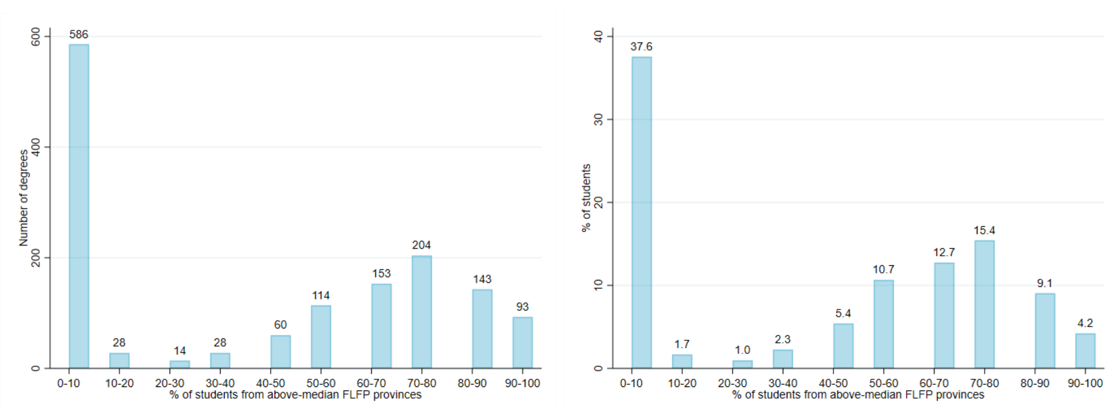
Notes. The table provides summary statistics regarding students' mobility for their studies. Besides mobility rates by gender, it provides information on the local gender culture in the province of studies of students. As this information is available for all students, the sample of female and male students include, respectively, 182,792 and 133,678 students.

TABLE A.7. Mobility to local labor markets by gender in the sample

	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 participationn (age:15-64)	54.6	9.7	66102	55.7	9.2	54400	0.0
Female/Male labor force participationn (age:15-64)	71.8	10.4	66102	72.9	9.8	54400	0.0
Female labor force participationn (age:25-34)	71.8	13.1	66102	73.1	12.2	54400	0.0
Female/Male labor force participationn (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 pref. for male workers	58.5	8.3	66102	59.3	8.0	54400	0.0

Notes. The table provides summary statistics regarding students' mobility to local labor markets one year after graduation. Besides mobility rates by gender, it provides information on characteristics of students' province of work. The sample includes female and male students who are employed at the moment of the follow-up survey, corresponding to 69,659 and 57,494 students. Decreases in sample size are due to missing information on the province of work for a small subset of individuals.

FIGURE A.2. Distribution of students from below-median FLFP provinces across degrees



(A) Distribution of degrees

(B) Students represented

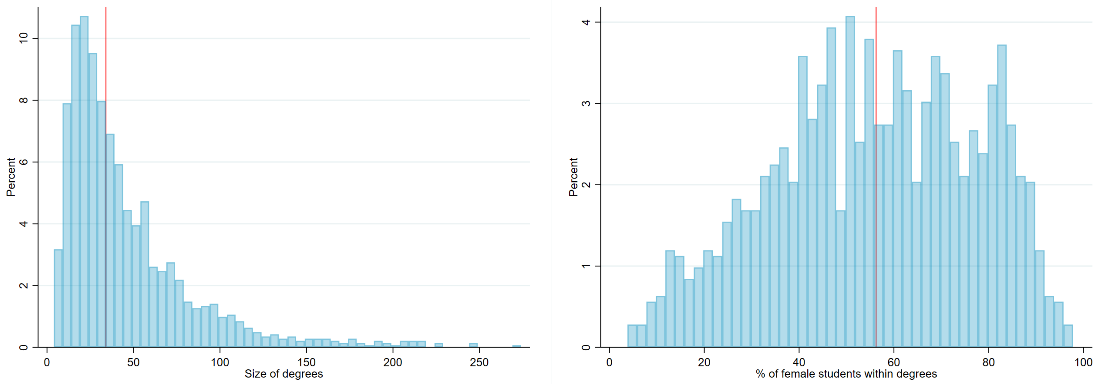
Notes. Panel (A) represents degrees by the % of students from above-median FLFP areas in 2016, categorized in brackets 0-10, ..., 90-100. One unit corresponds to a degree (N=1,572). Panel (B) shows the percentage of students represented by degrees that fall within each of these brackets.

TABLE A.8. Mobility patterns by gender culture 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 provides summary statistics regarding students' mobility in the sample of female students, contrasting students from provinces in the first vs. fourth quartiles of FLFP. Besides mobility rates by gender, it provides information on the characteristics of mobility in the sample of movers (57.8% and 63% of the two samples).

FIGURE A.3. Degree size and gender composition



(A) Size

(B) Share of female students

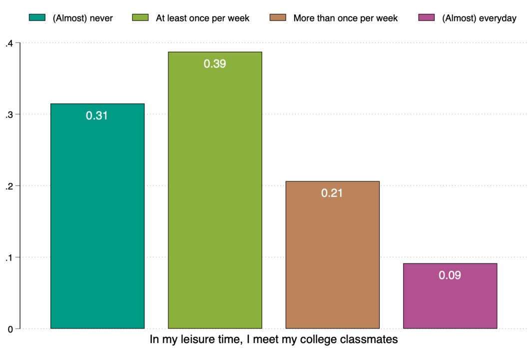
Notes. Panel (A) represents the distribution of degrees by their size. Panel (B) represents the distribution of degrees by the share of female students. The red lines correspond to the median. In both panels, one unit corresponds to a degree (N=1,572). Data refer to 2016.

TABLE A.9. Summary statistics of degree characteristics

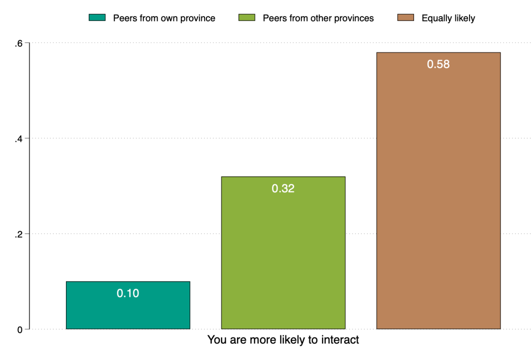
	Mean	SD	p50	Min	Max
Size of degree	47.0	43.0	34.0	4.0	410.0
% of female students	55.6	21.3	56.3	3.8	97.1
% of movers	55.3	23.2	56.3	0.0	100.0
% of movers (region)	28.5	23.1	25.0	0.0	91.7
% of students from above-median FLFP provs.	40.8	36.3	50.0	0.0	100.0
% of students with BSc at same univ.	72.9	22.6	78.4	0.0	100.0

The table presents summary statistics of the main degree characteristics, as represented by the average across all years (2012-2016). The unit of observation is a degree. There are 1,572 degrees in the sample.

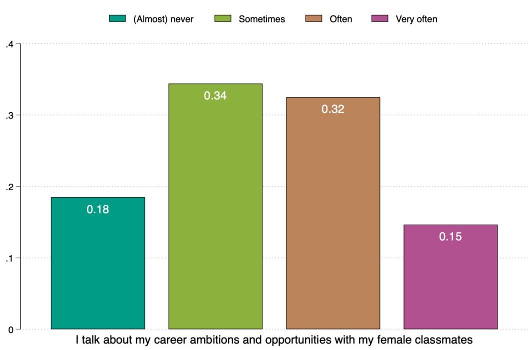
FIGURE A.4. Quantity and quality of social interactions



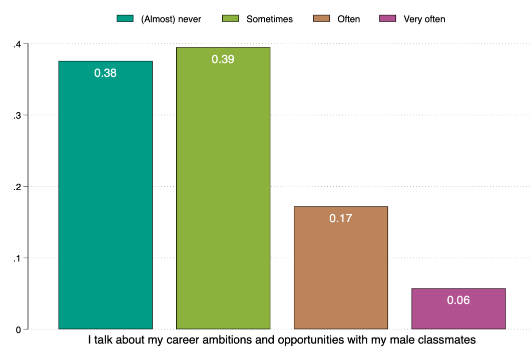
(A) Frequency



(B) Network structure



(C) Career opportunities



(D) Career opportunities

Notes. This figure displays survey responses from female students across various fields at the University of Bologna (N=490). Panels (A) and (B) reflect responses from first- and second-year students (as there are no meaningfull differences in the network structure over time). Panels (C) and (D) show responses from students at the start of their second year (N=171), given that students are significantly less likely to discuss career opportunities at the beginning of their first year.

TABLE A.10. Gender differences in the extensive margin of labor supply

	(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, after including degree and cohort fixed effects and controlling for their GPA. The dependent variables are as follows. 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 the type of contract. Column 3: indicator for whether a student is employed with a standard contract one year after graduation. Column 4: indicator for whether a student is employed with an internship contract. Standard errors are clustered at degree level.

TABLE A.11. The gender earnings gap at labor market entry, with controls 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

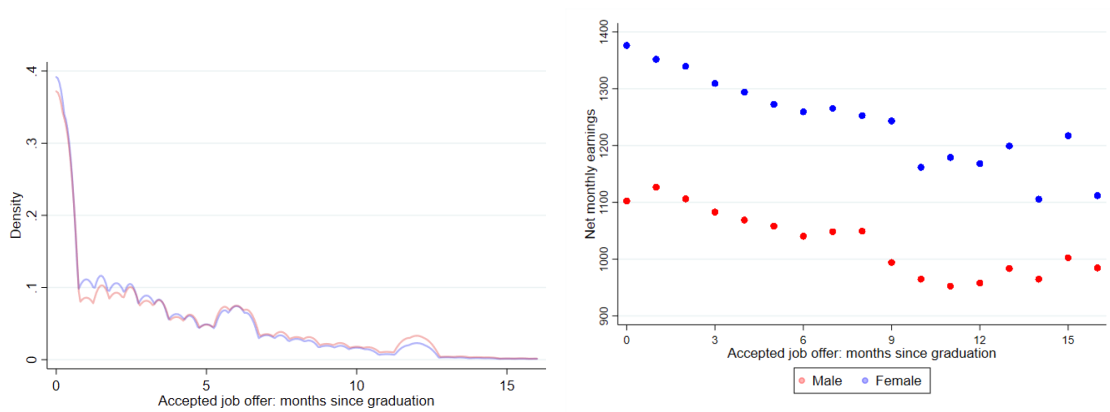
Notes. The table reports coefficients from regressions of graduates' labor market outcomes on a female dummy, after including degree and cohort fixed effects and controlling for covariates (GPA, prov. of work FEs, occupation FEs (20 classes), industry FEs (21 classes)). The sample consists of female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

TABLE A.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 their GPA. The sample consists of female and male students who are 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 A.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 A.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

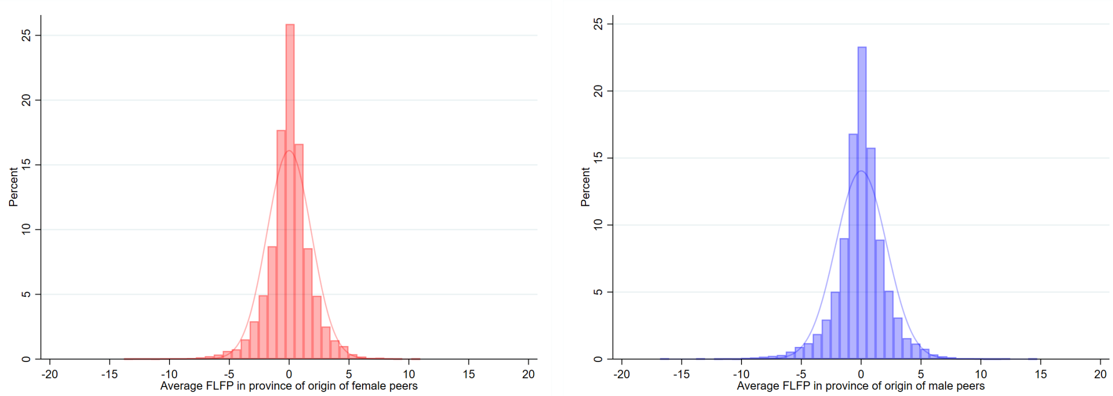
Notes. This table examines the selection-in terms of ability, educational histories and socio-economic background-of female movers (not working in province of origin) based on their province of birth, categorized by the FLFP (top versus bottom quartile). For each pre-determined characteristic, equation 1 is estimated. Predicted values for each group are presented in Columns 1 and 2, while Column 3 reports the p-value from a significance test on α.

TABLE A.14. Estimates of gender culture on men's labor supply at labor market entry

	(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.

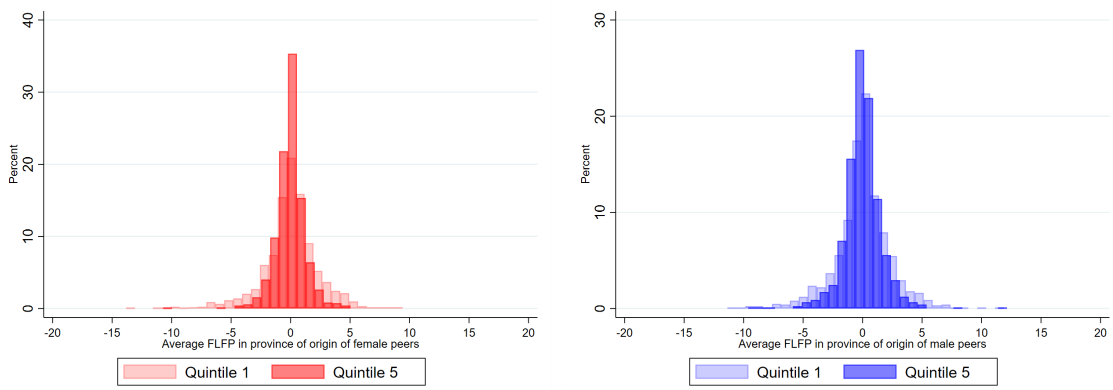
FIGURE A.6. Year-to-Year Variation in Students' Geographical Origins



(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 A.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 A.15. Balancing tests for cohort composition - Female students

Panel A. Educational history and ability

	(1) Age	(2) HS science	(3) HS humanities	(4) HS foregin 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 different regression, where the dependent variables are pre-determined covariate 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 female students in the sample (N=182,792). Variations in sample sizes across columns arise from missing information on some of the covariates (collected from the institutional survey). All regressors are standardised. Standard errors are clustered at degree level.

TABLE A.16. Balancing tests for cohort composition - Male students

Panel A. Educational history and ability

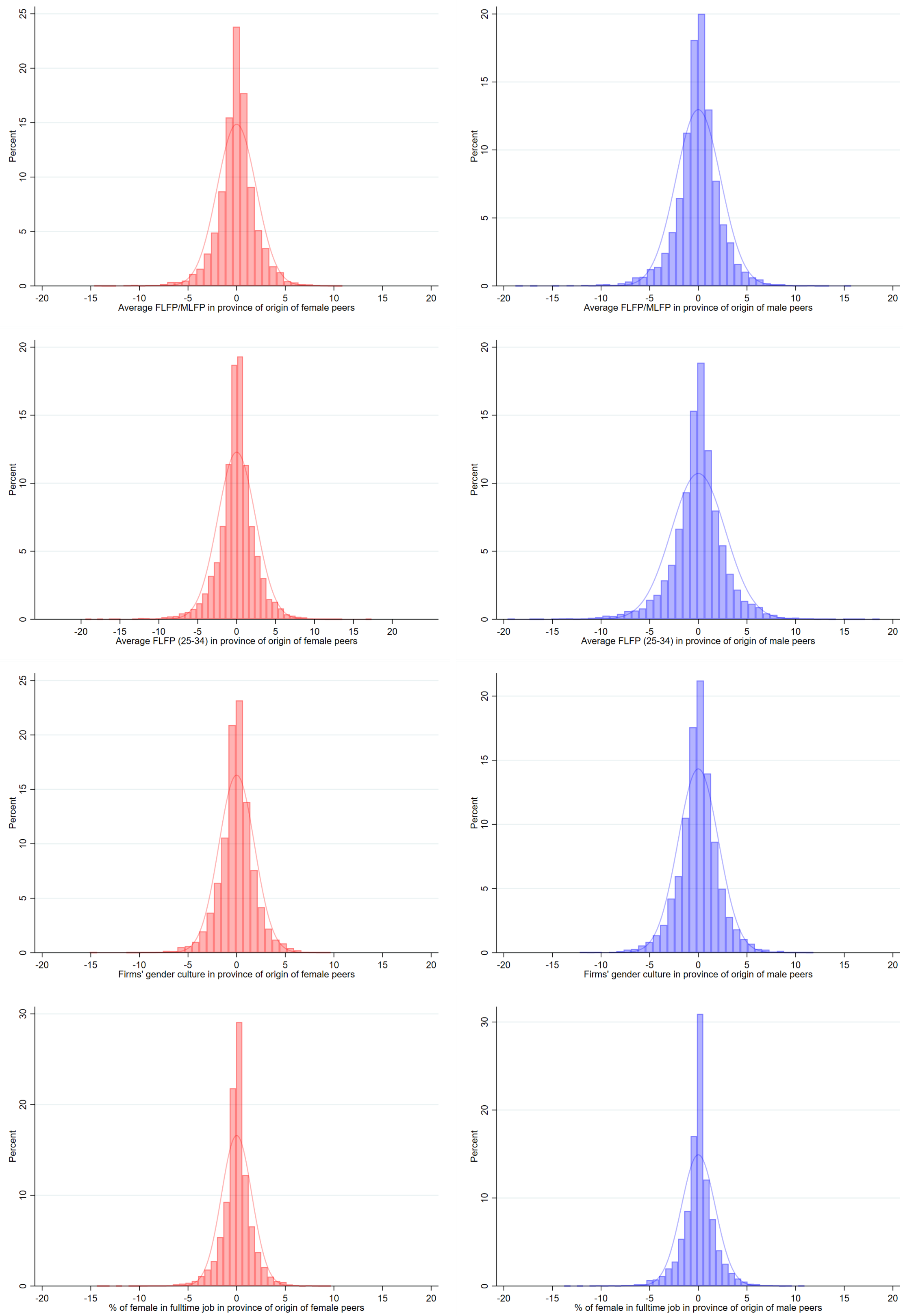
	(1) Age	(2) HS science	(3) HS humanities	(4) HS foregin languages	(5) HS social sciences	(6) HS vocational	(7) BSc grade	(8) Bsc grade > p50
(Mean)	(24.5)	(0.57)	(0.10)	(0.02)	(0.01)	(0.02)	(99.1)	(0.50)
$\hat{\delta}^{FP}$	0.045	0.010	-0.006	0.000	-0.001	0.000	0.239*	0.017**
	(0.059)	(0.006)	(0.004)	(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 covariate 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 degree level.

FIGURE A.8. Year-to-Year Variation in Students' Geographical Origins



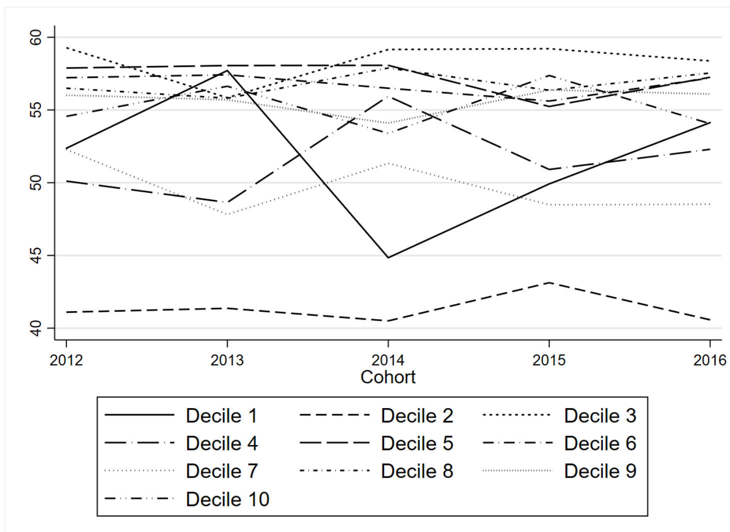
Notes. The figure plots the distribution of residuals from a OLS regression of the average characteristic in the province of origin of female (red) or male students (blue) on cohort and degree fixed effects. One observation corresponds to a degree-cohort pair. Histograms are presented by bins of 0.75.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

TABLE A.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
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: % of full-time female graduates in prov. 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: % of full-time female graduates in prov. 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 A.9. Time series of peers' characteristics by deciles of program's size



Notes. This figure plots the evolution in time series of the average FLFP in the province of origin of female peers within 10 randomly picked degrees. All programs were divided into deciles based on the average size across all years. One program was randomly chosen within each decile.

TABLE A.18. Raw and Residual Variation of Peers' Gender Culture 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 of female (Panel A) and male (Panel B) peers. These statistics are provided for groups of degrees categorized by quintiles based on the size of the degree programs. Quintiles are determined using the average size of programs calculated over five cohorts. The number of students in each program is indicated in parentheses next to the corresponding quintile. For instance, degrees in the first quintile include programs with fewer than 21 students.

TABLE A.19. Estimates of peer effects on female earnings and labor supply - Alternative Specification

	(1) Log(monthly earnings)	(2) Log(weekly hours)	(3) Pr(fulltime)	(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

Notes. Relative to the baseline specification, this includes controls for province of origin fixed effects, instead of the FLFP in the province of origin of the student. Regressions include cohort and degree fixed effects. 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.

TABLE A.20. Peer effects on survey response and probability of entering the labor market

Panel A. Female sample

	(1) Pr(response)	(2) Pr(work in first year)	(3) Pr(employed now)	(4) 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	-0.01*	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) Pr(response)	(2) Pr(work in first year)	(3) Pr(employed now)	(4) 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 (A) and men (B) on the probability of: (1) responding to the follow-up survey, (2) having been employed at least once during the first year, (3) being employed at the time of the follow-up survey (a condition for observing salary data), and (4) not reporting salary information in the survey (among those currently employed). Standard errors are clustered at the degree level, and all regressors are standardized. The sample in Column (1) includes all individuals (e.g., 182,792 women), reduced to those who responded to the follow-up survey in Columns (2) and (3), and to individuals who responded to the survey and are currently employed in Column (4).

TABLE A.21. Estimates of Peer Effects on Job Characteristics - Female sample

	(1) Permanent	(2) No contract	(3) Self-employment	(4) Public	(5) No-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 types of contract and sector 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. All the dependent variables are indicator variables. All the estimates are done on the sample of women 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 A.22. Estimates of peer effects on earnings and labor supply - Male sample

	(1) Log(monthly earnings)	(2) Log(weekly hours)	(3) Pr(fulltime)	(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 a regression of men'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. All the estimates are done on the sample of men 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.

TABLE A.23. Sensitivity to Measures of Gender Culture - 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 measures of peers' gender culture. The dependent variable in all columns is log(monthly earnings). Each column reports estimates for a separate regression, where I use the average of a different characteristic of peers' province of origin, as specified in the column labels. Regressions include degree (master x university) and cohort fixed effects. The estimates are done on the sample of 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 A.24. Estimates of Peer Effects on Female Earnings - Controls for Degree Trends

	(1) Log(monthly earnings)	(2) Log(weekly hours)	(3) Pr(fulltime)	(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. All the estimates are done on the sample of women 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 A.25. Estimates of Peer Effects on Female Earnings - Controls for Region Trends

	(1) Log(monthly earnings)	(2) Log(weekly hours)	(3) Pr(fulltime)	(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 studies)-specific linear time trends. All the estimates are done on the sample of women 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 A.26. Estimates of Peer Effects on Female Earnings Excl. Degrees with Trends in Size

	(1) Log(monthly earnings)	(2) Log(weekly hours)	(3) Pr(fulltime)	(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 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. The sample excludes degrees that experience trends in size over time.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 A.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 A.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 A.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, with an added control for an alternative peer characteristic, disaggregated by gender. For instance, in Column 1, I include controls 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 A.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 standardised. 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 A.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 standardised. 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 A.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 A.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 A.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 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. as 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.

TABLE A.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 students that participated in my 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. These statistics are reported for the overall sample (490 students), as well as for the two subsamples of female students from above-median (317 students) and below-median (173 students) FLFP provinces.

TABLE A.36. Baseline and Updated Beliefs on the Job Offer Distribution - Robustness Checks

	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 A.37. Beliefs on arrival rates of job offers and acceptance of part-time jobs

	(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 estimated coefficients from regressions of the elicited probability of accepting a part-time job offer 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 A.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.