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

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**Abstract**

Differences in labor market outcomes between men and women have been extensively documented. Yet, little is known about the role of peers in shaping these gaps, especially at the beginning of the career. This paper provides novel large-scale evidence on the effects of the social environment, as represented by college classmates, as a driver of women's early-career labor market decisions. I exploit unique administrative and survey data covering the universe of college students in Italy and cross-cohort idiosyncratic variation in peers' geographical origins within Master's programs. My findings indicate that exposure to female classmates originating from areas with egalitarian gender culture significantly increases women's labor supply, primarily through increased uptake of full-time jobs. A one standard deviation increase in peers' culture increases female earnings by 3.7%. The estimated peer effects are economically significant, comparing to more than a third of the gender earnings gap. Leveraging information on elicited job-search preferences, I present evidence that peers shape women's valuation of non-pecuniary job attributes. Moreover, analysis of original survey data on students' beliefs supports social learning explanations. I first show that the gender culture in a woman's province of origin shapes her beliefs on the relative arrival rates of part-time vs. fulltime jobs and her perceptions on employers' discrimination. Second, consistent with the predictions of a standard job search model, I provide evidence that these beliefs matter for women's acceptances of part-time jobs. Finally, I provide evidence of beliefs' updating. **JEL classification**: J31, J16, J22, R0, Z13.

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# 1 Introduction

Cultural norms are ubiquitous and shape payoffs from many individual decisions. One critical area where they are found to be particularly relevant is in the economic decisions of men and women. By shaping the beliefs and preferences of both genders, cultural norms largely contribute to gender disparities in labor supply and earnings (Kleven 2022, Ichino et al. 2022, Fernandez and Fogli 2009, Fernandez and Fogli 2006). Consequently, the persistence of gender norms prevents gender convergence in labor market outcomes (Kleven 2022, Fernandez 2013).

Understanding the determinants of cultural change is therefore a significant yet insufficiently understood problem. One hypothesis is that culture evolves through social learning (Fernandez 2013 and Fogli and Veldkamp 2011). Despite the popularity of these theories, the empirical evidence is scarce. This is primarily due to the scarcity of natural experiments that allow to study the driving forces of cultural evolution. In this paper, I exploit a unique natural experiment, together with comprehensive administrative and survey data on the universe of college students, to study cultural transmission from college classmates in the context of Italy. Specifically, I assess the effects of peers' culture on women's early-career labor market choices. I complement existing data sources with original survey data on students' beliefs to discern the mechanisms of peer influence.

Owing to features of this setting, university degrees can be thought to reproduce a *melting pot*, where students born in places with very different gender culture mix together within the same programs. Indeed, Italy is a salient example of a country with remarkable spatial differences in gender culture, as reflected in a variety of indicators, as self-reported gender attitudes, employment patterns and the magnitudes of child penalties (Campa, Casarico, and Profeta 2011, Casarico and Lattanzio 2023, Carlana 2019). The magnitude of these geographical differences is comparable to that of wide cross-country differences. For instance, the share of women (15-64) participating in the labor force ranges from $29\%$ to $67\%$ across provinces (NUTS 3 classification), and the share of firms reporting hiring preferences for male workers ranges between $29\%$ to $61\%$. A key feature of this setting is that a high share of students - around $57\%$ - migrate outside their province of origin to attend university. This allows the cultural composition of degrees to be very heterogeneous: in the median degree, half of the students are coming from above-median FLFP areas and the other half from below-median FLFP areas. Such a setting is therefore ideal to study how culture evolves when individuals migrate, and whether peers shape its evolution.

I start by establishing that gender culture in a woman's province of origin persistently shapes her labor supply decisions. I substantiate this claim relying on the epidemiological approach of Fernandez 2007 and re-adapting it to analyze within-country variations in cultural norms induced by movers, i.e. individuals who work in a different province than they were born, similar to Kleven 2022 and Kerwin, Guryan, and Pan 2024. The effect of culture is estimated based on the relationship between labor supply decisions for movers and gender culture in their place of birth. Results indicate that female movers originating from provinces with high FLFP have significantly higher labor supply compared to those from provinces with low FLFP, even when they work in the same local labor market and graduate from the same Master's program with the same grades. This difference is statistically significant and substantial, translating to an $8\%$ increase in weekly hours worked or a 2.5 percentage point higher likelihood of full-time employment. This relationship is unlikely driven by differential selection of movers from different areas. Importantly, the role of local culture is both quantitatively larger and not confounded by maternal role models, based on rich information on mothers' occupation and education level.

What happens to female labor supply decisions when women are randomly exposed to peers born in areas with different gender culture? Do they assimilate the culture of their peers or do they stick to the culture in which they were socialized early in life? I reproduce this experiment, by leveraging idiosyncratic variations in peers' geographical origins across different cohorts of students within 1,572 2-year Master's programs in 71 universities. This approach, first proposed by Hoxby 2000, rests on the assumption that there exists some variability in the composition of peer groups across adjacent cohorts within a degree program, which is beyond the control of individual students. I present several exercises that bolster the validity of this approach, by providing support to the identifying assumption that cross-cohort changes in students' geographical origins within programs are uncorrelated to time-varying unobserved determinants of earnings. Importantly, cross-cohort changes in peers' cultural composition are unrelated to a large battery of pre-enrollment student characteristics, such as their ability and family background.

My main finding is that exposure to peers from provinces with more egalitarian gender culture increases women's labor supply along the intensive margin, both through higher take-up of full-time jobs and increases in weekly hours worked. The magnitude of this effect is large: a one standard deviation increase in the culture of female peers (8.33 pps.) leads to a $3.3\%$ increase in their weekly hours and in a 1.9 percentage points increase in the likelihood of fulltime employment one year after graduation. This translates into a $3.7\%$ increase in their monthly earnings. These estimated peer effects are economically significant, comparing to $33\% - 41\%$ of the size of the gender differences in the same outcomes. Interestingly, peer effects are gendered: there is no effect from male peers. As a placebo, I reproduce the empirical analysis on the sample of male students. My findings indicate that peers do not influence men's earnings and labor supply, nor do they impact alternative job characteristics.

Moreover, I combine existing and newly collected data to shed light on the mechanisms of peer influence. First, I establish that the effects on women's labor market outcomes are not mediated by changes in academic performance and are not driven by changes in geographic mobility. Furthermore, I provide evidence indicating that peer effects are unlikely to operate through networks or referrals to firms. Instead, my findings indicate that the estimated peer effects operate through cultural transmission and social learning. First, relying on comprehensive data on students' rankings of job attributes, I provide evidence that peers contribute to changes in women's preferences, aligning with cultural explanations. Specifically, exposure to peers from more egalitarian culture decreases the importance that women attribute to non-pecuniary job factors, namely regarding hours flexibility and leisure time. Second, I present evidence that peer effects are strongly asymmetric: while women born in areas with below-median FLFP are positively influenced from exposure to more egalitarian classmates, the reverse does not happen. This indicates that women from more egalitarian areas don't assimilate the others' culture. In a stark rejection of conformism, these findings point to the existence of *spillover effects*, in the terminology of Boucher et al. 2022, consistent with social learning explanations.

To investigate the mechanisms of peer influence further, I have designed an original survey to elicit students' beliefs regarding gender attitudes and various future outcomes. This includes perceptions of employers' discrimination, beliefs regarding the distribution of job offers, and expectations of future fertility and child penalties. The survey also gathered information on the network structure and perceived peer influence. It was administered to a random sample of current female students across all disciplines at a single large university. With in-person administration and lottery incentives, I achieved a nearly $100\%$ response rate among attending students. I use this original survey (1) to investigate asymmetries in women's beliefs based on the gender culture in their province of birth, (2) test whether beliefs are predictive of job acceptance decisions, and (3) discern how beliefs evolve with the social environment. Relying on these data, I first show that the gender culture in a woman's province of origin shapes her beliefs on the relative arrival rates of part-time vs. fulltime jobs and her perceptions on employers' discrimination. Second, consistent with the predictions of a standard job search model, I provide evidence that these beliefs matter for women's acceptances of part-time jobs. Finally, comparing the evolution of beliefs before and after peers' exposure, I provide evidence of beliefs updating for women from less egalitarian areas.

This article contributes to several strands of literature. First, it relates to a longstanding literature that, since the seminal contribution of Fernandez 2007, has demonstrated the importance of cultural norms on women's lifetime decisions. Examples include women's labor supply (Fernandez and Fogli 2009), fertility (Alesina, Giuliano, and Nunn 2013, Fernandez and Fogli 2006), their marriage prospects (Bertrand, Cortes, et al. 2021), their take-up of childcare responsibilities (Ichino et al. 2022), among others. Recently, cultural explanations have been proposed for the persistence of large *child penalties* across countries (Kleven 2022, Cortés, Koşar, Pan, and Zafar 2022, Boelman, Raute, and Schönberg 2021). Most of these studies identify the role of culture by comparing the outcomes of immigrants within a host country. Variations in norms hence stem from cross-country differences. Furthermore, they usually focus on the general population of women, and on how culture interfere with women's (working) decisions around motherhood or marriage. In this paper, I focus on a narrower segment, i.e. young educated women, and exploit granular within-country variations in cultural norms. I provide novel evidence that culture plays a role on women's early-career choices, in a setting where I can rule out many potential confounders, among which, importantly, maternal influence.

Second, this paper contributes to the understanding of cultural transmission. Beside theories of intergenerational social learning (Fernandez 2013, Fogli and Veldkamp 2011), little is known on how social norms evolve and are transmitted. I contribute to filling this gap by providing empirical evidence on social learning from college peers. My findings indicate that the environment in which women are socialised in college plays a significant role on their early-career labor market choices. Previous empirical studies explored the role of social influence in shaping women's career decisions. Results from Olivetti, Patacchini, and Zenou 2020 and Mertz, Ronchi, and Salvestrini 2022 indicate that women's decisions to participate in the labor market and their occupational choices are shaped both by their mothers' behavior, and by that of other mothers in their close network. My paper is also complementary to some contemporaneous works that study the role of misperceptions in driving the stickiness of gender norms (Cortés, Koşar, Pan, and Basit 2022, Cappelen et al. 2023). Third, I connect to a literature that, since the seminal work of Bisin and Verdier 2000, has investigated the interplay between family and social influences (Patacchini and Zenou 2016, Patacchini and Zenou 2011). My results are indicative of cultural substitutability between peers and alternative family and social influences.

This paper also contributes to a broad body of work on gender gaps in the labor market. Recent evidence has shown that, in the skilled population, gender differences in the valuation of temporal flexibility, coupled with increasing returns to the provision of long hours, largely contribute to earnings inequalities (Cortes and Pan 2019, Zafar and Wiswall 2018, Blau and Kahn 2017, Azmat and Ferrer 2017, Flabbi and Moro 2012, Bertrand, Goldin, and Katz 2010). In accordance with previous work, I document that large differences in hours worked and earnings emerge between female and male graduates at labor market entry. My findings suggest that preferences for job attributes are endogeneous to the social environment and can explain part of early-career gaps. Specifically, I show that $30\%$ of the initial gap can be closed through peer influence. Finally, my paper contributes to a rising literature that has incorporated beliefs in job search models (Jäger et al. 2024, Cortes, Pilossoph, et al. 2022, Mueller and Spinnewijn 2023, Conlon et al. 2018).

The rest of the article is organized as follows. The next section describes the context. Section III presents the data. Section IV provides descriptive evidence on gender gaps in early-career labor market outcomes and discusses fertility. Section V describes the empirical strategy and support to its validity. Section VI presents the main findigs on average treatment effects. Section VII discusses estimates from a battery of robustness exercises. Section VIII explores non-linearities in peer effects. Section IV concludes.

# 2 The College Melting Pot

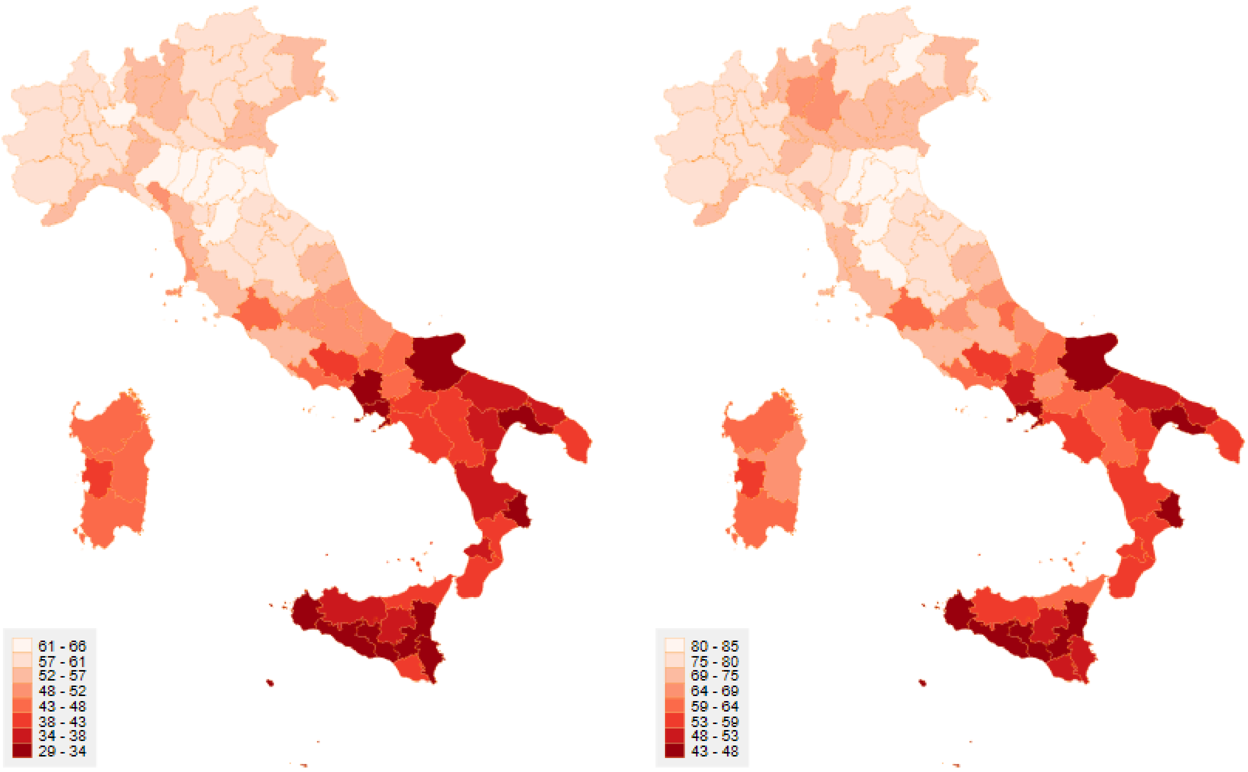
## 2.1 Geographical heterogeneity in gender culture

Since the seminal contribution of Fernandez and Fogli 2009, many studies have assessed the importance of cultural norms on a variety of socio-economic outcomes by relying on cross-countries differences in cultural norms, through the immigrant population in a host country[1]. Recently, this approach has been used in tandem with more granular within-country variations in gender culture, through the behavior of movers within a country (Kleven 2022, Boelman, Raute, and Schönberg 2021). Likewise, this paper exploits granular, yet very wide, geographical variations in cultural norms in Italy. Differences in gender culture across Italian provinces are substantial, and their magnitude is comparable to wide cross-country differences. These are reflected in a variety of indicators, from self-reported gender attitudes to several indicators of labor market attachment (Campa, Casarico, and Profeta 2011, Carlana 2019, Casarico and Lattanzio 2023, Carrer and Masi 2024). For example, the shares of citizens that disagree with statements as "*Being a housewife is just as fulfilling as working for pay*" or "*Men should be given priority when jobs are scarce*" range from $16\%$ to $67\%$ across Italian regions (NUTS 2), according to answers to recent waves of the European Value Survey (EVS 1990-2008). Likewise, traditional labor market outcomes differ substantially by gender across provinces. For instance, the share of women between 15-64 (25-34) years of age participating in the labor force ranges from $29\%$ to $67\%$ ($38\%$ to $86\%$) across provinces (NUTS 3), while these outcomes vary far less for men (e.g. between $64\%$ and $82\%$ in the age group 15-64). A graphical representation of the labor force participation of women between 15 and 64 years of age is shown in Figure 1 (Panel a). This is based on past values, i.e. averages between 2004 and 2007, when students in the sample were in adolescence and, hence, exposed to these local social norms. The distribution is highly heterogeneous across space: in some areas, the FLFP is as low as $29\%$, mirroring that of low-income countries, while in some others significantly higher shares of women are in the labor force, in line and even beyond the OECD average. The mean (standard deviation) of female LFP is $51\%$ (11). One important concern is that these spatial variations could reflect differences in labor market conditions rather than gender culture. I therefore

[1]See: Ichino et al. 2022, Fernandez and Fogli 2006

contrast female and male labor force participation and plot the ratio between the two in Panel b. If local labor market conditions were a major driving force, we would expect the ratio to be more uniformly distributed across space. Instead, its geographical distribution mirrors that of the female LFP alone, and it has a wide variance. These differences are sizeable even for young women (24-34 years old), as depicted in Figure 3 (Appendix): the share of women participating in the labor force ranges from $38\%$ to $86\%$.

Figure 1: Heatmaps of female labor force participation




(a) Female LFP (%)

(b) Ratio of female to male LFP (%)

The maps present the female LFP (Panel a) and the ratio of female to male LFP (Panel b) across provinces in Italy. Individuals between 15 and 64 years of age are considered. Each geographical partition is a province (NUTS 3 classification) and there are 103 provinces in total. Both measures are constructed as averages of years 2004-2007. Source: Labor Force Survey (Istat).

Moreover, similar spatial patterns are also observed on other indicators of gender culture, such as firms' culture and individual attitudes towards gender roles, as shown in Figure 4 (Appendix). Figure 5 show that there is a high correlation between female labor force participation and alternative measures of gender culture. Since my measure of culture is thought to capture societal role models to which students were exposed before university, I rely on past values of female LFP and I take the average between 2004 and 2007, a period that spands though students' adolescence.

Throughout the paper, I will focus on provinces as a geographical unit. A *province* is an administrative division of intermediate level between a municipality and a region, that corresponds to the NUTS-3 classification[2]. Assignment of students to provinces is based on their province of residence at the enrollment date, as recorded in university registers. Such province should be interpreted as the area where the student grew up.
Thhroughout the paper, I will rely on the following measures of culture:

1. Female labor force participation (15-64) between years 2004 and 2007 (NUTS 3);

2. Ratio of FLFP/MLFP (15-64) between years 2004 and 2007 (NUTS 3);

3. Using this dataset, I construct a map of local opportunities for men and women using labor market outcomes of stayers (students who work in the same province they were born in) and I compute the share of women who are employed full-time (NUTS 2), using data of graduation dates between 2013 and 2016 ;

4. Ratio of share of women vs. men employed full-time (NUTS 2);

5. firms' gender culture, computed as the share of firms with no hiring preferences for male workers.

**Students' mobility**. A key feature of this setting is that the majority of students move away from their province of origin to attend university (ANVUR 2023). This phenomenon has longstanding origins and has been rather stable over time. In the years of this analysis, around $58\%$ ($31\%$) of students moved to another province (region) to pursue university. Importantly, there are no major differences in the share of movers between men and women (Table 3). To better understand the strong migration of students outside their province origin, it is useful to provide a description of the institutional setting in Italy. When focusing on public institutions only (covering over $90\%$ of students), Master-level

[2]Notes: The average population of a province was 551,000 as of 2010, but there is large heterogeneity. The largest province, Rome, has over 4 million residents and contains 121 different municipalities. The smallest province, Ogliastra (Sardinia), has less than 60,000 residents and only includes 23 municipalities.

degrees were offered in 89 universities in 2016. However, their distribution is concentrated in a subet of 52 provinces, out of a total of 103 (Figure **??**). Moreover, since some universities are only specialized in specific subjects, not all fields of study are offered in all institutions. For example, as Figure **??** shows, only a subset of universities (29 or 24) have degrees in information technologies or in agriculture and veterinary (Figure **??**). Because of the unequal distribution of universities across provinces, around $20\%$ of Italians aged 18-19 don't have any institution of higher education in their province of residence and around $77\%$ have both STEM and non-STEM schools **??**. Students apply to universities regardless of their place of residence. A large majority of universities are public and semi-public. Tuition fees are set autonomously by each academic institution. Students from low-income families receive scholarships that cover part or the full amount of tuition fees and some living expenses. Eligiblity criteria are set at the regional level[3].

This allows for the composition of degrees to be highly diverse: the median degree accounts for $50\%$ of movers, and this share ranges from $12\%$ to $94\%$. Two other features of this setting are especially valuable: (i) students spend (at least) two entire years in the same degree, and (ii) the size of Master degrees is relatively small. $50\%$ $(25\%)$ of degrees count less than 34 (20) students (Figure 2). Given the relatively small size of degrees, college classmates likely constitute a relevant peer group.

## 3 Institutional background

**Admission to Master's degrees**. Since the early 2000s, degrees are organized as bachelor's (three years) and master's (two years)[4]. Most students enroll in a two-year master's program after completing a three-year bachelor's degree. Admission criteria for master's programs are determined autonomously by each academic institution. However, certain fields or programs, such as medicine, health-related fields, architecture, psychology, and primary education, are subject to selective national entry exams under Law 264/1999. A common requirement across institutions is that admission to a master's program is con-

[3] Rattini 2022.

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

ditional upon having completed a bachelor's degree, and it also typically requires the fulfillment of curricular prerequisites, defined as credits in mandated courses. Therefore, students have the flexibility to change fields between the bachelor's and master's levels, subject to meeting the eligibility requirements. On average, students must acquire 77 constrained credits to enter a master's program, although there is substantial variation across fields of study. For instance, any student wishing to enroll in a master's program in economics must have completed at least 53 credits in economics, statistics, and other social sciences (Brandimarti 2023). In addition to eligibility requirements, admission policies may include entry exams or selection processes based on bachelor's grades or interviews. In practice, many programs have a fixed number of seats, and admission is often based on a selective process where applicants are ranked according to their academic proficiency. Procedures vary across universities and fields, but typically these rankings take into account an applicant's score on an entry exam or grades obtained during their bachelor's studies. Usually, a minimum bachelor's GPA is required. Programs may also have additional requirements, such as English proficiency if the program is taught in English, motivation letters, or reference letters.

**Tuition fees**. 90% of students in Italy are enrolled in public universities (ISTAT 2016). Tuition varies depending on the degree, the university, and family income. Need-based grants are available for students from low-income families. Regional governments determine the income threshold for eligibility for these grants. Depending on the family's financial situation, these grants can cover tuition fees, as well as provide housing and meal vouchers. On average, 23% of students in my sample receive need-based grants. For students who are not eligible for these grants, the average annual tuition fee is €1262, as reported by (Commission/EACEA/Eurydice 2016).

# 4 Data and sample selection

The empirical analysis relies on two main sources of data. The primary source comprises administrative and survey data, which collectively cover 93% of the universe of college students in Italy, obtained from the AlmaLaurea consortium. Specifically, the dataset encompasses all students enrolled in 1,572 2-year Master's degree programs across 71 universities, spanning enrollment cohorts between 2012 and 2016. This database consists of administrative data from university records, institutional survey data, and post-graduation follow-up surveys, as described hereafter.

1. **Administrative student-level information**, from university records, for all students. This includes students' socio-demographics, such as municipality of birth and residence, measures of academic performance (e.g., GPA and graduation grade), as well as unique identifiers of Master's programs within universities and enrollment and graduation dates. Importantly, I use this source to identify college classmates and construct measures of their gender culture based on their birth province. Due to the administrative nature of the data, all information is available for the entire student population, ensuring that I observe the characteristics of all peers.

2. **Institutional pre-graduation survey.** Universities administer this survey to all students as part of the graduation process. At the end of their final year, students are required to complete a compulsory survey, with a response rate close to $100\%$. This survey collects detailed information on students' job search intentions and preferences, including their valuation of various job attributes. Additionally, the survey gathers data on students' socio-economic background, including parents' occupations and education levels, as well as measures of family income. Furthermore, it collects detailed information on students' educational histories, such as previous education in high school and Bachelor's degree programs, their grades in previous education, and the working activities they participate in during their studies.

3. **Follow-up surveys.** Students are contacted by the AlmaLaurea consortium for follow-up surveys one, three, and five years after graduation. While participation in these surveys is voluntary and does not involve monetary incentives, the response rate remains high (e.g., $74\%$ after one year). Table 2 compares observed characteristics between respondents and non-respondents, coming from the administrative data and the institutional survey. These surveys gather comprehensive information on realized job characteristics, such as monthly earnings, weekly hours worked, contract type (part-time vs. full-time), job security, occupation, industry, and location. Additionally, they include retrospective information on the job-search process and current job search activities.

**Sample costruction.** In this paper, I use data on enrollment cohorts between 2012 and 2016. Since data are collected from graduating cohorts, I recostruct enrollment cohorts using students' enrollment and graduation dates from university records. A student's classmates, or peers, are defined as all students who enroll in the same university major, or degree, in the same cohort, and who remain enrolled for the entire duration of the Master[5] My sample is composed of students from an unbalanced panel of Master degrees that exist for at least 2 consecutive years and that count at least one man and one woman in the same cohort. These two restrictions eliminate around 3% of the original sample. The final sample is composed of 316,470 students from 1,572 degrees and 71 universities. The analysis on labor market outcomes is conducted on the subsample of students that participate in the follow-up survey (74%). In Table **??**, I present differences in observable characteristics between the entire sample and the subset of respondents to the follow-up survey. Summary statistics of the main variables are presented in Table 3 and Table **??**.

**Original survey on students' beliefs**. To investigate the mechanisms of peer influence, I have designed an original survey to elicit students' beliefs regarding gender attitudes and various future outcomes. This includes perceptions of employers' discrimination, beliefs regarding the distribution of job offers, and expectations of future fertility and child penalties. The survey also gathered information on the network structure and perceived peer influence. It was administered to a random sample of current female students across all disciplines at a large university. With in-person administration and lottery incentives, I achieved a nearly 100% response rate among attending students. Detailed information on the survey and elicitation methods is provided below.

# 5 Two Novel Facts About Early-Career Gender Gaps

## 5.1 The early-career gender earnings gap

Despite women achieving higher levels of human capital accumulation, as reflected in their higher college attendance and GPA, they fare significantly worse than men at the on-

[5] A drawback is that I lose track of dropouts, which account for 6% of the enrolled students between 2012 and 2016 (ANVUR 2023).

set of their careers. One year after graduation, equally productive women earn $11\%$ less than their male counterparts from the same Master's program (Table 5). This gap is both statistically significant and economically meaningful: it represents €1,915 every year, on average. This 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 $8\%$ fewer hours per week compared to male students of comparable academic performance. These differences are not attributable to geographic mobility and are only mildly related to differences in occupational and industry sorting by gender (Table 6). Furthermore, while the results are presented at the mean, these patterns persist across fields of study, albeit with varying magnitudes. The residual gap in hourly wages, however, is much smaller at $2.8\%$. These findings provide comprehensive evidence of systematic gender differences in earnings among the high-skilled population in Italy.

**Fertility and couple decisions**. Importantly, while the focus of a recent strand of literature has been on the role of motherhood in driving reductions in women's labor supply (Kleven 2022, Kleven, Landais, and Søgaard 2019, Bertrand, Goldin, and Katz 2010), I can rule out realized fertility as a major factor. In the sample, the average age is 25, with only $3\%$ of women having children, and $13.5\%$ either married or cohabiting with a partner. Removing these two groups from the sample does not alter estimates of the gender earnings gap (Table 7).Additionally, analysis of expectations data from the original survey indicates that women, on average, expect to have their first child at 31, which is consistent with the national average.

## 5.2 Cultural persistence

Gender culture in a woman's province of origin persistently shapes her labor supply decisions. I substantiate this claim, relying on the epidemiological approach of Fernandez 2007 and re-adapting it to analyze within-country variations in cultural norms induced by movers, similar to Kleven 2022 and Kerwin, Guryan, and Pan 2024. To isolate the influence of culture from other local factors such markets and institutions, I examine the working behaviors of female movers using information on province of residence before entrance in college and province of work. Movers are defined as individuals who work in a different province than they were born. The effect of culture is estimated based on the relationship between labor supply decisions for movers and gender culture in their place of birth. The fundamental idea underlying this analysis is straightforward: movers to the same work province share the same market conditions and institutional settings, but they may not necessarily share the same cultural beliefs and preferences. In Table 8, I compare the labor market outcomes of female movers depending on the quartile of gender culture in their province of origin, controlling for the province of work and degree and cohort fixed effects (Columns 2 and 5). The results indicate that female movers originating from provinces with high FLFP have significantly higher labor supply compared to those from provinces with low FLFP, even when they work in the same local labor market and graduate from the same Master's program with the same grades. This difference is statistically significant and substantial, translating to an 8% increase in weekly working hours or a 2.5 percentage point higher likelihood of full-time employment. While these results are striking, a threat to causal interpretation is that movers born in low-FLFP and high-FLFP provinces might differ in other dimensions that impact their labor market outcomes. To investigate the importance of such concerns, Table 11 provides descriptive statistics on movers by province of birth. The table shows that movers from high-FLFP provinces are similar to movers from low-FLFP provinces, e.g. in their previous and contemporaneous academic performance, in their socio-demographics and their socio-economic background. This attenuates concerns of differential selection of movers into degrees by province of birth and provides further credibility to the epidemiological approach. Another concern arises from the possibility that additional local factors, such as economic activity or general labor market conditions, are correlated with spatial disparities in female labor force participation. Should these factors influence the beliefs and preferences of individuals, the estimated relationship might not purely reflect the effects of local gender culture. To explore this possibility, I present an epidemiological analysis focusing on the subsample of male students in Table 10. While there is some positive relationship between the gender culture in males' province of origin and their working hours, the magnitude of the coefficients is less than half of those observed for women.

While in this section I am agnostic on the precise sources of gender norms, I will later present evidence of systematic differences in beliefs between female movers born in high-FLFP versus low-FLFP areas, using data from the original survey.

**A unique experiment to study cultural assimilation**. What happens to women's labor supply decisions when they are randomly exposed to peers from a diverse cultural background? Do they assimilate the culture of their peers or do they stick to the culture in their province of origin? This setting, coupled with unique data on the universe of students, allows to reproduce this experiment at a large scale and explore the drivers of cultural change. In practice, this paper aims to identify the causal effect of peers' culture on women's labor market outcomes. Additionally, leveraging detailed information from the main data source and original survey data on students' beliefs, I provide evidence on the mechanisms through which peer influence operates.

# 6 Identification Strategy and Empirical Model

The main threat to the identification of peer effects relates to *selection*, or endogeneous peer formation. This arises because individuals choose their majors and universities, and hence their peer groups. As a result, the characteristics of the peers they are exposed to are likely correlated with their unobserved characteristics that plausibly affect their success in the labor market, leading to *correlated effects* in the Manski terminology (Manski 1993). In the absence of randomization of students into peer groups, which is unlikely to happen at a large scale, my identification strategy overcomes the selection issue by leveraging idiosyncratic variation in peers' geographical origins across different cohorts of students within a Master's program. This approach has been first proposed by Hoxby 2000 to assess the impact of classmates gender and race on students' outcomes, and has been subsequently widely used in studying peer effects in education (Cattan, Salvanes, and Tominey 2022, Mertz, Ronchi, and Salvestrini 2022, Cools, Fernandez, and Patacchini 2022, Olivetti, Patacchini, and Zenou 2020, Carrell, Hoekstra, and Kuka 2018, Lavy, Paserman, and Schlosser 2012, Lavy and Schlosser 2011, Bifulco, Fletcher, and Ross 2011). This strategy allows students to select in universities and programs based on their knowledge of their average composition. However, the strategy relies on the intuition that there exists some variability in the composition of peer groups across adjacent cohorts within a degree program, which is beyond the control of individual students. In other words, students cannot perfectly predict the composition of their actual cohort within a Master's program. I provide two tests to assess whether this key identifying assumption holds in practice. The features of the data structure are crucial for implementing this empirical approach. Specifically, the data include students from a vast array of Master's programs (1,572) and span multiple enrollment cohorts from 2012 to 2016. Therefore, they are ideal for exploiting cross-cohort changes in peers' geographical composition within degrees to estimate the impact of peers' culture on women's early-career outcomes in the labor market. The empirical model can be written as:

$$Y_{idc} = \theta_d + \alpha_c + \gamma FLFP_{idc} + \delta^{FP}\overline{FLFP}^{FP}_{-i,dc} + \delta^{MP}\overline{FLFP}^{MP}_{i,dc} + \left(\sum_{k=1}^{K}\beta_k x^k_{idc}\right) + \varepsilon_{idc} if Female = 1 \tag{1}$$

$$Y_{idc} = \theta_d + \alpha_c + \gamma FLFP_{idc} + \delta^{FP}\overline{FLFP}^{FP}_{i,dc} + \delta^{MP}\overline{FLFP}^{MP}_{-i,dc} + \left(\sum_{k=1}^{K}\beta_k x^k_{idc}\right) + \varepsilon_{idc} if Female = 0 \tag{2}$$

where i denotes the individual, d denotes the degree within the university, and c denotes the cohort. The main outcomes of interest are monthly earnings and hours of work, as well as alternative job's characteristics. I estimate the empirical model on the two subsamples of female and male students separately and I allow for gender-specific peer effects. In the subsample of women, the treatment variables of interest are $\overline{FLFP}^{FP}_{-i,mc}$ and $\overline{FLFP}^{MP}_{i,mc}$, i.e. average past values of the FLFP in the province of origin of female and male peers, respectively. These are the sample moments of the leave-one-out distribution of past female LFP in the province of origin of students who belong to a specific gender, degree and cohort:

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

It's important to note that the leave-one-out strategy introduces a mechanical negative correlation between the female labor force participation (FLFP) in an individual's own province of origin and the average FLFP among same-sex peers[6] This is accounted for by

[6] To illustrate this, consider two female students in the same degree and cohort. If one student comes from a city where 30% of women participate in the labor market, while 60% do so in the province of origin of the other student, the first student will naturally be exposed to a higher mean FLFP across female peers compared to the second student, even if they are exposed to the same set of peers.

controlling for $FLFP_{idc}$ in the regression[7]. $\varepsilon_{ifc}$ is the error term, which is composed of a degree-specific random element and an individual random element.

The inclusion of degree fixed effects $\theta_d$ accounts for time-invariant endogenous sorting into majors within universities, and cohort fixed effects $\alpha_c$ control for confounding factors at the national level, affecting the labor market outcomes of all students in a given cohort. Finally, in some specifications, I control for a set of individual covariates: these include pre-determined characteristics, such as grades in previous education, age at enrollment, parents' occupations and education, or contemporaneous achievements. I cluster standard errors at the major level to account for unobserved correlation of error terms within majors.

The parameters of interest are $\delta^{FP}$ and $\delta^{MP}$. OLS estimates will be unbiased if $\overline{FLFP}^{FP}_{-i,mc}$ and $\overline{FLFP}^{MP}_{i,mc}$ are uncorrelated with unobserved determinants of students' earnings. For equations (1) and (2) to yield valid causal estimates of these paramaters, the key identifying assumption is therefore that cohort-to-cohort variation in peers' geographical origins is random within degrees. This assumption is likely to hold given the rules governing university admission in Italy. More than $55\%$ of Master's degrees are selective, i.e. admission is limited to a fixed number of students. Typically, admission rules are decided by universities and involve an entrance exam, a standardized test, or consideration of average grades from the Bachelor's degree. In selective programs, variation in $\overline{FLFP}^{FP}_{-i,mc}$ and $\overline{FLFP}^{MP}_{i,mc}$ come from year-to-year variation in the geographic origins of students whose admission score are high enough to be admitted into a program.

## 6.1 Validity of the identification strategy

**Threat to identification.** One critical concern in identifying peer effects is the presence of *correlated effects*, in the Manski terminology (Manski 1993). In essence, similarities in economic outcomes among individuals within a peer group may stem from shared individual characteristics or common institutional or economic shocks, rather than from social influence alone. In practice, this translates into the possibility that cross-cohort changes in students' geographical origins within master's programs can correlate with time-varying unobserved determinants of students' labor market outcomes. For example, this could oc-

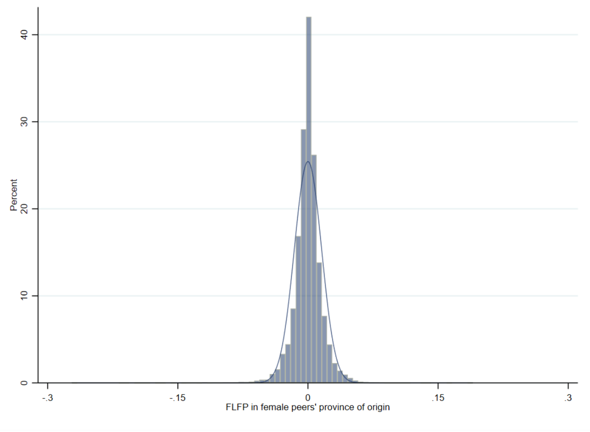
[7]In a sensitivity analysis I estimate a model in which I control for province of origin FEs

cur if labor market trends in a specific region influence the applicant pool for universities in that region, or if shifts in the student composition within a program impact the selection of new students. If this happens, then $\overline{FLFP}^{FP}_{-i,mc}$ and $\overline{FLFP}^{MP}_{i,mc}$ are correlated with time-varying determinants of outcomes $\varepsilon_{idc}$, leading to biases in $\delta^{FP}$ and $\delta^{MP}$. For this identification strategy to effectively capture social influence, it is crucial that these cross-cohort fluctuations are effectively random. The objective of this section is to examine the validity of this identifying assumption through a series of checks.

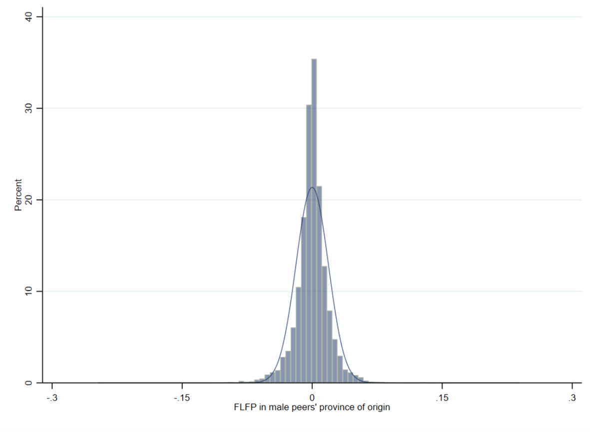
**Balancing tests for cohort composition.** One empirical test of this assumption is to verify that there is no selection, based on observables, into peer groups. Precisely, while students can select into fields of study and universities based on time-invariant characteristics - such as the average peers' composition - I need to rule out that students systematically sort into programs based on the specific composition of their cohort. To assess the plausibility of the key identifying assumption that time variant and unobservable factors are not driving the results, I test whether there is systematic selection based on a wide range of observable student characteristics. Specifically, I perform an extensive set of balancing checks in which I test whether the peer composition in a Master's cohort is systematically related to a large vector of high-quality measures of student background characteristics observable in the institutional data. For these placebo tests, I pick as characteristics pre-determined covariates, that cannot be causally affected by peers but that might be correlated with unobserved characteristics of other students enrolling in the same programs. These characteristics include academic performance in previous education (e.g., Bachelor's degree or high school grades), and indicators of family socio-economic status, derived from detailed information about the occupations and educational backgrounds of both parents. Tables ?? and ?? present the results of these placebo checks on the subsamples of female and male students, respectively. They report OLS estimates from equations 1 and 2. Each column corresponds to a different regression, where the dependent variable is a different predetermined covariate. Results indicate that none of the estimated correlations appear to be significantly different from zero in the model, indicating that the exposure to peers from egalitarian provinces in the Master is unrelated to outcomes measured before entry in the Master. I take this as encouraging indication that the treatment variable is unlikely to be correlated with other time-varying unobservable individual determinants of labor market outcomes. In fact, drawing from Altonji, Elder, and Taber 2005, we can reasonably infer that the degree of selection on observable characteristics serves as a reliable indicator of the degree of selection on unobservables.

**Identifying variation**. This identification strategy rests on the assumption that cross-cohort changes in students' geographical origins within a master's program are idiosyncratic. Where do they come from? In selective programs, where admission is based on entry exam scores or bachelor's GPA, variations in $\overline{FLFP}{-i,mc}^{FP}$ and $\overline{FLFP}{-i,mc}^{MP}$ arise from fluctuations in the geographical origins of students whose position in the ranking is sufficiently high for admission to a specific program. This design assumes that such variations are idiosyncratic, conditional on the student's bachelor's GPA. In contrast, in non-selective programs, year-to-year changes in the geographical origins of students stem from shifts in the applicant pool's composition. Evidence from the balancing test confirms that cross-cohort changes in $\overline{FLFP}_{-i,mc}^{FP}$ and $\overline{FLFP}_{-i,mc}^{MP}$ are not related to changes in the students' academic quality, as measured by students' grades in the bachelor. As a further randomization check, I inspect whether the variation in students' geographical composition is consistent with variation that we would expect with natural random fluctuations. Figure 2 plots the average FLFP in peers' provinces, with separate panels for female peers (Panel a) and male peers (Panel b), after absorbing degree and cohort fixed effects. Figure 6 in the Appendix does the same using the ratio of FLFP to MLFP as an alternative measure for culture. Deviations in the average FLFP closely follow the normal distribution, which I plot for comparison. The shape of the distribution further supports the idea that the proportion of female peers is as good as random, conditional on the included controls. Implementing this empirical strategy further requires that there is enough variation in peers' geographical composition across cohorts within a master's program to obtain precise estimates of our parameter of interest. Table 14 reports moments from the distribution of peers' culture, as measured by the FLFP in the province of origin. The standard variation of the average FLFP in the provinces of female (male) peers' provinces is 8.33 (8.45) percentage points in the raw data, and is reduced to 1.97 (2.1), once I net it out from degree and cohort fixed effects. This means that around one fourth of the total variation in peers' culture is left unexplained: I rely on this variation to estimate peer effects. All the estimates are very precisely estimated.

Figure 2: Year-to-Year Variation in the Average FLFP in Peers' Provinces




(a) Female peers




(b) Male peers

Notes: The figure plots the residuals from a regression of the average FLFP in the province of origin of female (Panel a) or male peers (Panel b) on cohort and degree fixed effects. It is plotted against the normal distribution for comparison. Each degree-cohort represents one observation.

**Other checks.** The evidence presented in the balancing tests lends support to the hypothesis that year-to-year changes in students' geographical composition are not stemming from selection. However, it does not completely rule out the possibility that concurrent institutional changes, such as shocks to local labor markets, (that might, even coincidentally, correlate with changes in students' composition) could influence outcomes across cohorts of students. To address these concerns, I augment the model by including region times year fixed effects, which helps account for any time-varying regional factors that could influence outcomes. Results are presented as part of the robustness checks.

# 7 Main Results

**Effect of peers on female earnings and labor supply**. Estimates of the empirical model, as described by equations (1) and (2), on the subsample of female students are presented in Table 15. The outcome variables are monthly earnings, weekly hours worked and hourly wages, all in logarithmic forms, and an indicator of fulltime employment. In the baseline specification, I include degree, i.e. master times university, and cohort fixed effects and I cluster standard errors at the degree level. Regressors are all standardised.

Results indicate that exposure to peers from provinces with more egalitarian gender culture increases women's 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 the culture of female peers (8.33 pps.) leads to a $3.3\%$ increase in their weekly hours and in a 1.9 percentage points increase in the likelihood of fulltime employment one year after graduation, a $2.5\%$ increase relative to the mean. This translates into a $3.7\%$ increase in their monthly earnings. These estimated peer effects are economically significant, comparing to $33\% - 41\%$ of the size of the gender differences in the same outcomes. Interestingly, peer effects are gendered: there is no effect from male peers.

**Effect of peers on women's occupational choices**. In Table 16, I present estimates of peer effects on the types of occupations and industries women work in one after graduation (Columns 1-4). I classify occupations (or industries) as high-earnings or high-fulltime in two steps. First, I separately rank occupations (or industries) based on their (i) median earnings or (ii) share of full-time jobs. Second, I define one occupation (or industry) as high-earnings, or high-fulltime, if it ranks above median, or above the mean, in the relative distributions of (i) and (ii). I use these four indicators as outcome variables. According to these estimates, exposure to female peers from high-FLFP provinces affects women's occupational choices (Columns 1-2). A one standard deviation increase in peers' culture leads to a 1.7 percentage points increase in the likelihood of choosing an occupation with high earnings, equivalent to a $4.4\%$ increase relative to the mean. Also in the case, the effect is only coming from female peers. To quantify the importance of changes in occupations in explaining the rise in women's labor supply, I re-estimate the empirical model on weekly hours worked augmenting it with occupation and industry fixed effects. Although the estimated coefficient $\delta_{FP}$ has decreased by approximately one third, the coefficient on weekly hours remains large and statistically significant, suggesting that changes in occupations account for only a portion of the increase in women's labor supply.

**Effect of peers on other job characteristics**. While exposure to female peers from high-FLFP provinces significantly impacts women's labor supply and earnings, it does not appear to influence other job characteristics. Notably, hourly wages remain unaffected (Table 15, Column 4), and there is no meaningful effect on the industry where the woman is employed. In Figure 7, I present estimates of the empirical model on a set of other job's characteristics, such as whether the employer operates in the public versus private sector, or the type of employment contract. Interestingly, women do not appear to be influenced along any of these dimensions.

**Effect of peers on male outcomes**. As a placebo, I reproduce the empirical analysis on the sample of male students. If the FLFP in a student's province of origin is primarily a proxy for her gender culture, I would not expect peers' gender culture to have a direct effect on men's labor supply and earnings. Indirect effects, e.g. in the form of spillovers, could instead materialize, for example if some men feel the pressure from women's improved aspirations. Results on male students are presented in Table 17. Exposure to female or male peers from high-FLFP provinces has no impact on men's earnings, nor on weekly hours and the likelihood of fulltime employment. Peers of both genders have only small positive effects on men's hourly wages.

# 8 Robustness checks

This section has two key goals. The first is to show that similarities in labor market outcomes among female classmates within a program are driven by peer influence and do not reflect spurious relationships. The second goal is to provide robust evidence that can answer the following question: *Is it peers' culture that matters?*

**Effects of the social environment.** Results from a large number of balancing tests (Section 5) provide convincing evidence that there is no systematic selection of students into peer groups. Specifically, they lead to conclude that cross-cohort variations in classmates' composition within a degree are to be considered as good as random. Still, they don't fuly rule out that similarities in labor market outcomes among female classmates arise because of correlated effects, such as common economic shocks that might incidentally correlate with changes in peers' composition.

## 8.1 Sensitivity analysis

In this section, I test the robustness of my findings across different sub-samples. I investigate whether the results vary among samples defined by major size and the proportion of students who completed their Bachelor's degree at the same university. The results, as presented in Table ??, are highly robust.

**Heterogeneity by degree size**. First, a concern is that my identification strategy may not be valid in very small programs, where students may be more likely to know higher shares of their peers from previous education. Column (2) indicates that the benchmark estimates are unchanged when dropping degrees in the bottom $5\%$ of the size distribution (where, on average, there are fewer than 12 students per degree). This suggests that the benchmark estimates are not influenced by noise or possible endogenous peer formation stemming from very small degrees. Second, estimated effects are larger than those in the benchmark specification when degrees in the top decile of the size distribution are dropped (where, on average, there are more than 89 students), as indicated in Column (3). In this category of large programs, the effects vanish, and standard errors become very large, as shown in Column (4). Lastly, estimated peer effects are more pronounced in degrees with sizes below the mean (44 students). This aligns with the notion that smaller degrees entail a lower risk of students segregating themselves into distinct social networks, possibly by their background characteristics, thus resulting in reduced beneficial social interactions among group members, as in Carrell, Sacerdote, and West 2013.

**Heterogeneity by proportion of students with Bachelor at the same institution**. Another concern arises in degrees where a significant portion of students completed their Bachelor's degree at the same institution. In such cases, students may have moved together from a shared Bachelor's program to a shared Master's program. This could result in cross-cohort variation in peers' origins being driven by selection rather than being idiosyncratic. To address this concern, I exclude degrees where the vast majority of students completed their Bachelor's at the same institution (Column 6). The estimates remain robust after this exclusion. Additionally, I provide results from the empirical model on a sample of degrees where the proportion of students who completed their Bachelor's at the same institution falls within the bottom $25\%$ (Column 7). Despite the significant reduction in sample size, the estimated effects are larger in magnitude than the benchmark estimates and precisely estimated.

**Heterogeneity by student attendance to classes**. As a placebo, I conduct the analysis focusing on the subset of students who do not attend classes in the Master's program. This subset is identified through the pre-graduation survey, where some students report working full-time for the entire duration of the Master's program, constituting $8.7\%$ of the sample. Since these students likely have limited interactions with their peers, peer effects within this subgroup should be minimal. The results of the analysis regarding heterogeneity by students' attendance are detailed in Table 19. As expected, the findings reveal significant heterogeneity in the effects of peers: while the peer effects are substantial for students with high attendance to classes, there is no evidence of an effect for students with low attendance.

## 8.2 Robustness exercises

This section has two primary goals. The first is to show that similarities in labor market outcomes among female classmates are driven by peer influence and do not reflect spurious relationships. The second goal is to provide robust evidence that can answer the following question: *Is it peers' culture that matters?*

**Effects of the social environment.** Results from a large number of balancing tests (Section 5) provide convincing evidence that there is no systematic selection of students into peer groups. Specifically, they lead to conclude that cross-cohort variations in classmates' composition within a degree are to be considered as good as random. Still, they don't fuly rule out that similarities in labor market outcomes among female classmates arise because of correlated effects, such as common economic shocks that might incidentally correlate with changes in peers' composition. I investigate this possibility by adding region (of study) times cohort fixed effects to the main specification. Results are presented in Table **??**. Estimates are unchanged in this specification, which rules out the possibility that similarities in outcomes are driven by common shocks.

Finally, I want to rule out that previous results are driven by noise coming from specific degrees, such as (i) very small degrees, (ii) very large degrees or (iii) degrees with low inflows of movers. To this end, I corroborate previous findings by showing that estimates are robust when excluding from the sample degrees that are in the first or in the fourth quartile in the size distribution[8] or degrees that are in the first quartile in the share of movers from other provinces[9] (Table **??**).

**Is it peers' culture that matters?** Previous sections have established that (i) cross-cohort variations in peers' geographical composition within a degree are not stemming from systematic selection of students into peer groups, (ii) that similarities in labor market outcomes among female classmates are not driven by common regional shocks, (iii) nor by noise generated by either too small or too large degrees. These tests provide compelling evidence that reduced-form estimates of $\delta^{FP}$ and $\delta^{MP}$ are able to measure the effects of the social environment rather than spurious relationships. Even in a setting that allows to give a causal interpretation to these two parameters, an important question is: *What is the characteristic of peers that matters?* Owing to the richness of the data source, I am able to rule out that the effects of culture are confounded by a large set of alternative peers' characteristics. Indeed, one natural concern is that students originating from different provinces can differ in important dimensions, including the respective processes of selection into educational paths. For example, they might differ with respect to their abilities, their family income or background, or the maternal role models they were exposed to. In Table **??**, I report descriptive statistics on observed individual characteristics for movers originating from provinces in the first vs. fourth quartiles of lagged FLFP. The two groups are observationally similar along many observed dimensions, e.g. pre-determined ability, contemporaneous achievements, parental education and family composition. One exception is the maternal labor supply, which is strongly positively related to the FLFP in the province of origin. In Table **??**, I replicate the empirical analysis by controlling for alternative peers' characteristics[10]. Estimates of $\delta^{FP}$ and $\delta^{MP}$ are not affected by the inclusion of these controls, which rules out that the effects of culture are confounded by alternative relevant peers' characteristics, including ability - measured by grades in previous education - maternal role models and family composition. Finally, results are unchanged when I rely on the ratio of FLFP/MLFP as an alternative proxy for culture (Table **??**).

[8]In order to create a distribution of degree size, for each degree I define its size as the minimum size in the years of analysis (2012-2016)

[9]To create a distribution for the share of movers, I consider the minimum share of movers across five enrollment cohorts.

[10]Note that the analysis is performed on the subsample of female students with non-missing information on parents' occupations and on previous grades (around 90% of the whole sample)

# 9 Mechanisms

## 9.1 What peers don't do

The previous section provides evidence indicating that peers' gender culture significantly affects women's labor market decisions at the beginning of the career and that these effects are sizeable. Plausible mechanisms, which finds support in the data, are cultural transmission and social learning from classmates, that I will discuss this channel in detail in a separate section. However, there are alternative plausible channels through which these effects could operate. In this section, I will discuss these alternative channels in detail.

**1. Human capital**. We have seen before that the FLFP in a student's province of origin is not a proxy for a student's ability (Table 11): women from provinces in the highest vs. lowest quartiles of FLFP do not differ in their in their observed ability, as measured by their grades in previous education (e.g. the Bachelor), and in their GPA and graduation grades in the Master's program. However, one concern is that local characteristics in the province of origin could affect students on other unobserved dimensions, such as their motivation. If this is the case, and women from high-FLFP areas are high types in these unobserved factors (which could just justify why they have better labor market outcomes), then exposure to higher shares of those individuals is likely to impact students' effort. To test this channel, I replicate the empirical analysis using indicators of women's academic performance as outcomes, as presented in Table 20. Specifically, the outcome variables include GPA in the Master's program (scale 0/30), the graduation grade (scale 66/110), and an indicator of delayed graduation (*fuoricorso*). Sample averages of these variables are provided in the table. Results indicate that there is no significant effect of peers on women's academic performance. The coefficients are not statistically different from zero, and the estimated magnitudes are economically insignificant. For instance, a one standard deviation increase in the culture of female peers is associated with a 0.071-point increase in students' graduation grade, representing a negligible $0.06\%$ increase relative to the mean. Based on this evidence, I rule out that human capital acts as a mediating factor in improving women's outcomes in the labor market.

**2. Geographic mobility and networks to local labor markets**. Another plausible explanation is that exposure to peers from high-FLFP provinces directly influences women's decision on where to look for a job. For instance, women from high-FLFP areas might share information about their local labor markets, or friendships formed could prompt women to follow their peers into these labor markets. If either of these channels operates, the geographic origins of a woman's peers should impact her decisions regarding geographic mobility. To test this prediction, I use characteristics of the local labor market where a woman ends up working as outcome variables in the empirical model described by equation (1). Results indicate that the geographic origins of peers, as measured by the FLFP in their province of origin, do not affect women's mobility decisions (see Table 21). The outcome variables examined include the FLFP in the province of work, an indicator of whether a woman is working in the same region where she studied or elsewhere, an indicator of whether a woman is working abroad, and an indicator of whether a woman is working in a province different from her birth province. Sample averages of these variables are provided in the table. A few descriptive facts regarding women's mobility are worth noting: on average, $68\%$ of students find their first job in the same region where they studied, $5\%$ work abroad, and the remainder work in a different region than where they studied, possibly their province of origin. Among students who migrated to another province for their studies, $39\%$ return to their province of origin, with notable differences observed across quartiles of gender culture: women from the highest quartile of FLFP are nearly twice as likely to move back to their province of origin compared to female students from the lowest quartiles. Results from Table 21 indicate that exposure to peers from high-FLFP provinces does not influence women's mobility decisions, such as choosing to work in the region where they studied or deciding to work outside their birth province. None of the estimated coefficients is statistically different from zero, and the magnitudes of the estimates are small. Furthermore, the results remain robust when fixed effects for the province of employment are included in the baseline specification of equation (1), as shown in Table 22. When comparing women working in the same province, exposure to female peers from high-FLFP areas leads to a $3.7\%$ increase in monthly earnings. Taken together, these findings suggest that the observed effects on female earnings and labor supply cannot be attributed to changes in women's geographic mobility.

**Networks**. Another plausible explanation is the role of peers as networks to access better firms. Unfortunately, the available data do not include firms' identifiers, which prevents a formal test of whether, and to what extent, networks contribute to the estimated peer effects. However, I provide suggestive evidence indicating that they are unlikely to be a major driver of increases in women's labor supply. The basic idea of this test is simple: cross-cohort changes in the average female labor force participation (FLFP) in peers' provinces within a degree could correlate with changes in the relative shares of students who are local or movers. Here, "local" refers to students who study in their province of birth. Suppose that locals have better connections to local firms. If (i) the cross-cohort variation in peers' gender culture is correlated with changes in the shares of locals in a program and (ii) peers serve as networks to better firms, then estimates of the effects of peers' culture would be biased upwards. To test this hypothesis, I also control for the shares of female and male peers who are locals in the main specification. Results are presented in Table 23. Estimates of the effects of peers' gender culture remain robust and increase slightly in magnitude.

## 9.2 Cultural transmission and learning

A candidate explanation for the estimated peer effects is that peers affect the beliefs and preferences of women in a way that influence their labor market behavior, a phenomenon I refer to as cultural transmission. In this section, I present evidence of changes in self-reported preferences. In the following section, I will delve into social learning explanations by providing evidence of changes in beliefs.

**Change in preferences**. I rely on data on students' rankings of job attributes obtained from the institutional survey administered by universities to all graduating students. Due to the survey's compulsory nature, the response rate is nearly $100\%$, providing data on the valuations of job attributes for the entire population of college graduates. This is a unique of this dataset compared to previously used survey data from small samples of students from selected fields and universities. In the survey, students are asked to rank various job attributes, expressing their preferences on a scale from 1 to 5. Using individual responses, I construct indexes measuring students' preferences for specific types of job attributes, such as those related to pecuniary aspects (e.g., salary and career progression) or flexibility (leisure time and hours flexibility). These indexes are computed as unweighted averages of scores attributed to the separate job characteristics. Additionally, I create separate indicators for each job attribute based on whether the student assigns the maximum value (5/5) to each of them individually. I use these measures as outcome variables in the empirical model. Results are shown in Table 24. Note that indexes have been standardised. Findings indicate, when socialized in cohorts with more women from high-FLFP provinces, women report attributing less importance to non-pecuniary job factors, particularly flexibility (Column 2). These findings offer suggestive evidence of changes in women's preferences, aligning with cultural explanations. Moreover, consistent with previous results, male peers do not seem to influence women's preferences for jobs.

**Asymmetric peer effects**. The linear-in-means model used in the analysis assumes that everyone in the group is linearly affected by the mean peers' characteristic. In the framework of Boucher et al. 2022, this arises if the underlying mechanisms is conformism. Under the former, agents derive utility from conforming to the social norm generated by their peers' actions and, therefore, act to minimise the distance between their behavior and the social norm. If conformism is the correct microfoundation, peer effects should be symmetric. Figure 8 presents treatment effects (average FLFP in provinces of female peers) by quartiles of gender culture in a woman's province of origin. Peer effects are strongly asymmetric: while women born in areas with below-median FLFP are positively influenced, in their earnings and labor supply, from exposure to more egalitarian classmates, the reverse does not happen. This indicates that women from more egalitarian areas don't assimilate the others' culture. In a stark rejection of conformism, these findings point to the existence of *spillover effects* from one group to another, in the terminology of Boucher et al. 2022. This strong asymmetry is consistent with social learning explanations. I provide evidence of beliefs' updating in the next section.

# 10 Original survey on students' beliefs

The primary objective of this survey is to complement existing data sources and gain a deeper understanding of the mechanisms of peer influence. Specifically, the key goals are (1) to investigate potential asymmetries in women's beliefs based on the gender culture in their province of birth, (2) test whether beliefs are predictive of job acceptance decisions, and (3) shed light on possible beliefs' updating.

**Gender culture and women's beliefs.** Since the seminal contribution of Fernandez 2007, numerous papers have argued that the gender culture in a woman's country/region of origin or ancenstry shapes her beliefs, thereby influencing her labor market choices (Boelmann, Raute, and Schönberg 2023, Kleven 2022, Ichino et al. 2022, Olivetti, Patacchini, and Zenou 2020, Fernandez 2013, Fogli and Veldkamp 2011). While previous studies propose hypotheses about which beliefs are influenced by the environment—such as beliefs regarding gender identity or the costs of working - all of these studies are essentially agnostic regarding the precise sources of gender norms. Conceptually, in this context, we can think of the gender culture in a woman's province of birth as affecting a wide array of beliefs: for example, beliefs about the role of women in society, perceptions regarding employers' discrimination, beliefs on the job offer distribution, as well as expectations about long-run outcomes, such as the age of fertility and expectations regarding the child penalty. All of them, in turn, could influence the labour supply decisions of young women and, particularly, the acceptance of part-time job offers. I have designed this survey to elicit women's beliefs regarding these various aspects. In this section, I will first present evidence of disparities in beliefs stemming from local gender culture and show how these differences translate into acceptances of part-time jobs. I will offer a theoretical illustration of the mechanisms by which these beliefs affect women's decisions to accept part-time jobs. Furthermore, I will present evidence of beliefs' updating.

**Survey implementation.** I have conducted the survey among graduate students currently enrolled at 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.

To construct a sample of analysis, I have randomly selected a sample of Master's degree programs and, within each program, I have randomly chosen one course from the first semester in 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. Specifically, upon 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[11]. To incentivize participation, students had the chance to enter three lotteries with gift cards worth €100 [12]. The response rate reached 97% among attending students. Based on calculations on AlmaLaurea data, around 77% of students attend classes regularly. It's important to note that 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. A total of 899 students 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.

**Sample selection and description.** I exclude from the sample students who are on Erasmus or attending a bachelor's program (less than 1%), as well as international students or students with missing information on the country/province of origin (5.8%). The number of female students in the resulting sample is 490. Among them, 319 are in the first year of the Master's program, and 171 are in the second year. The proportion of students originating from another province (region) is 89% (70%). A description of the fields of study

[11]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.

[12]The gift cards were generic and could be used across multiple brands or providers, to prevent that the choice of a specific provider could affect selection

and summary statistics of this sample are presented in Table 25 and 26.

## 10.1 Beliefs about job offer distribution

**Elicitation.** Students' beliefs about the job offer distribution have been elicited through hypothetical scenarios that aim at reproducing a realistic setting of job search:

1. *Consider the following scenario: you have graduated from this Master's program and you start searching for a job. You send 10 applications to jobs that are coherent with your studies. Consider that, when you apply to jobs, you don't know the working conditions (monthly salary and whether it is a part-time vs. a full-time contract*[13]*).*

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

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

- On a scale from 1 (my answer is very close to the true probability) to 5 (I answered at random), what is the degree of uncertainty when answering to the previous questions? ($\boldsymbol{\sigma^F}$)

2. *While you are waiting for answers to your applications, one employer contacts you and offers you a part-time position (28 hours/week) with a net monthly salary in line with your expectations. You have to decide whether you accept the job offer or you wait for the answers to the other applications. What do you think is the probability you are going to accept this part-time job offer?* Give your answer on scale 0-100.

**Asymmetries in beliefs based on gender culture in the province of origin.** In the first panel of Table **??**, I show how baseline beliefs on the job offer distribution differ based on the local gender culture in a woman's province of origin. Specifically, these are the beliefs elicited at the beginning of the first year of the Master, aiming to capture the student's initial perceptions before any influence from peers. Table **??** reports the predictions from a linear regression of each dependent variable on degree fixed effects and an indicator denoting whether a woman originates from a province with below-median or above-median. First, there are no meaningful differences in the expected arrival rate of job offers ($\alpha$) between women born in areas with below vs. above median FLFP. Out of ten applications, women born in low-FLFP and high-FLFP provinces expect to receive, on average, 3.21 and 3.52 job offers, respectively. However, there is a striking asymmetry

[13]Notice that in Italy, 91% of online vacancies don't mention salary/salary range, precise information on working hours is limited (Burning glass data)

in the expected relative arrival rates of part-time vs. full-time jobs. Upon receiving one job offer, women from low-FLFP areas expect a significantly higher likelihood of receiving a part-time relative to a full-time job offer (+6.45 pps.). This gap is substantial, comparing to a 12.6% increase relative to women from high-FLFP areas. Consistently, women born in low-FLFP areas are 7 percentage points more likely to accept a part-time job offer, a 12% increase relative to their peers from high-FLFP areas. These differences cannot be attributed to differences in their geographic preferences, as these results are robust to controlling for the expected location of the job.

**Beliefs' updating.** Panel 2 of Table ?? shows differences in the same beliefs observed one year later, during the second year of the program. While there is little evidence of beliefs being updated regarding the overall arrival rate of job offers, the results suggest significant updates in beliefs about the relative arrival rates of part-time versus full-time job offers. Specifically, women born in low-FLFP provinces revise their beliefs downwards regarding the probability of receiving a part-time offer relative to a full-time one. This leads to a substantial narrowing of the gap with their counterparts from high-FLFP areas, who exhibit only minor updates in their beliefs. Coherently, women from low-FLFP areas become less likely to accept part-time jobs, closing the gap with their counterparts. These results provide evidence of asymmetric beliefs' updating, which is consistent with the asymmetry in the estimated peer effects. While I cannot quantify the contribute of peers relative to other social influences in the process of beliefs' updating, these results suggest social learning as a plausible mechanism behind peer influence in this setting.

**Beliefs matter for acceptances of part-time jobs.** Consider an economy where two types of jobs exist: part-time and full-time jobs, each characterized by a fixed number of hours. Consider a simple random search model, where in each period individuals face an exogeneours arrival rate of jobs $\alpha$, of which $\gamma_P$ are part-time. Individuals have beliefs on the relative arrival rates of part-time vs. full-time jobs ($\tilde{\gamma_P}$). Consider, for simplicity, that employment is an absorbing state and that there is no on-the-job search. A job-seeker's decision to accept a job offer is determined by the reservation earnings property. Therefore, each job offering earnings above the reservation value are accepted.

$$R = \frac{b + \frac{\alpha\left((1-\tilde{\gamma_P})(1-F^F(R))w^F_{avg} + (\tilde{\gamma_P})(1-F^P(R))w^P_{avg}\right)}{r}}{1 + \frac{\alpha\left((1-\tilde{\gamma_P})(1-F^F(R)) + \tilde{\gamma_P}(1-F^P(R))\right)}{r}} \tag{3}$$

Since $\frac{\partial R}{\partial \tilde{\gamma_P}}$<0, a testable prediction of the model is that higher expected likelihood of receiving a part-time job offer induces higher acceptance of part-time jobs, by decresing the reservation earnings. Figure 10 plots the relationship between these beliefs and the probability of accepting a part-time job offer. The correlation between the two variables is high: a one standard deviation increase (23 pps.) in the expected probability of receiving a part-time offer translates into an increase in the acceptance rate of part-time jobs by more than a third of a standard deviation.

# 11 Conclusions

Gender differences in earnings and labor supply are pervasive across labor markets, industries and occupations. These reflect in large part differential sorting of men and women towards jobs and firms. Using data on the universe of college graduates in Italy, I document the existence of a large gap in entry-level earnings between equally productive male and female students who graduate from the same degree. This gap largely reflects differential sorting towards job types. Specifically, net of degree fixed effects, women are more likely employed in part-time jobs and work fewer hours than their male counterparts. Differences in labor supply cannot be explained by realised, nor anticipated, fertility in the first five years of labor market experience. Rather, female sorting towards low-hours and low-earnings jobs strongly relates to the culture prevailing in their province of origin, as proxied by past values of female LFP. In this paper, I provide novel large-scale evidence on the role of the social environment, as represented by college classmates, in shaping women's job preferences and early-career labor market choices. Leveraging data on the universe of students from 1,572 Master degrees in Italy (2012-2016), my identification strategy exploits plausibly exogeneous cross-cohort changes in peers' geographical composition within a degree. My findings indicate that the exposure to peers with more egalitarian gender culture affects women's career choices, above and beyond the role of own culture. A one standard deviation increase in peers' culture increases female earnings by 3.7%, mostly through through increases in the labor supply happening both within and across occupations. Furthermore, I shed light on a novel mechanism: leveraging rich data on elicited job-search preferences, I find that peers exert an influence over women's aspirations, as stated before they start looking for a job. Women in more egalitarian cohorts attribute lower value to non-pecuniary job attributes, such as hours flexibility and leisure time. I find evidence of strong asymmetries in peer influence. Peer influence is especially strong towards women who lack alternative role models, such as women raised in provinces with low female LFP or grown up in families with non-working mothers. Conversely, women with more egalitarian gender attitudes do not assimilate the culture of peers from more conservative backgrounds, consistent with spillovers mechanisms. These results yield important implications on gender inequalities: because male students are not affected by peer influence, peers reduce early-career gender gaps by 30%. Moreover, based on newly collected survey data on a sample of students, I shed light on two novel facts. First, the gender culture in a woman's province of birth shapes her perceptions on employers' discrimination and her beliefs on the arrival rates of job offers. More precisely, women born in places where low shares of women participate in the labor force (i) expect higher discrimination from employer and (ii) significantly underestimate the probability of receiving a full-time job offer compared to women born in places with high FLFP. Secondly, one channel through which peer effects operate in this context is through social learning: specifically, women from less egalitarian areas update their beliefs on offer arrival rates and converge to the beliefs of their classmates from more egalitarian areas. Consistent with the predictions of a job search model, learning on arrival rates of job offers reduces the gap in the acceptance of part-time jobs between the two groups.

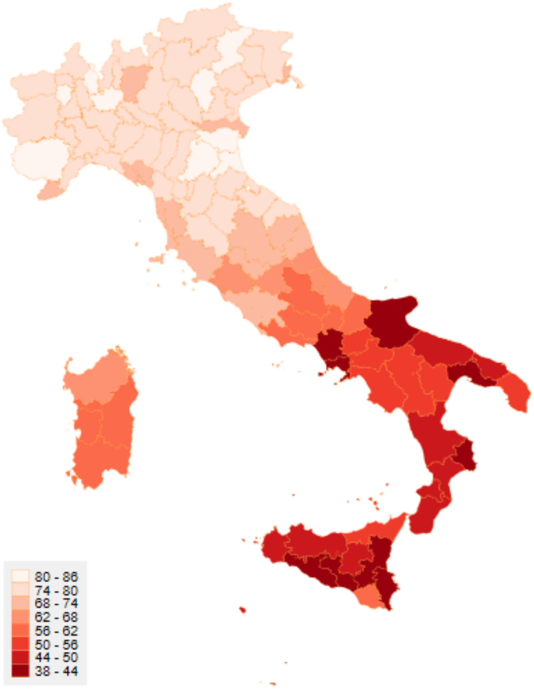
# APPENDIX

Table 1: Summary statistics - Measures of gender culture

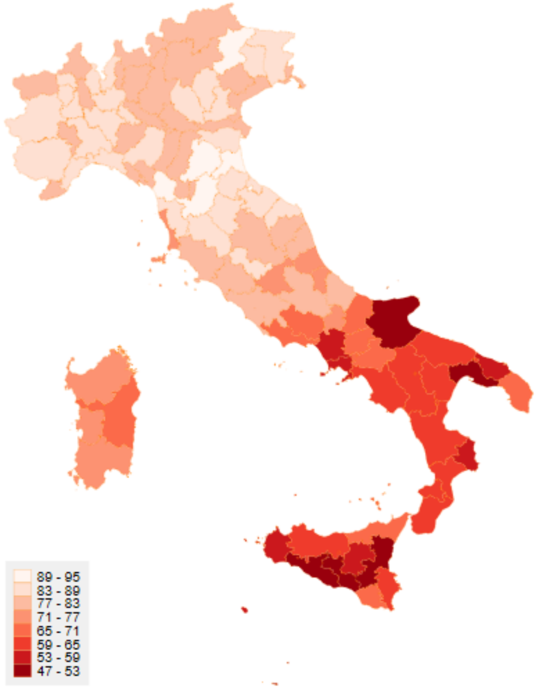
| Variable | Mean | Median | SD | Min | Max | N |
|---|---|---|---|---|---|---|
| *Labor force participation* | | | | | | |
| Female labor force participation (age: 15-64) | 51.35 | 56.03 | 10.13 | 29.89 | 66.66 | 103 |
| Female labor force participation (age: 25-34) | 67.84 | 74.45 | 14.03 | 38.24 | 86.43 | 103 |
| Female/Male labor force participation (age: 15-64) | 68.56 | 72.02 | 10.70 | 43.62 | 85.69 | 103 |
| Female/Male labor force participation (age: 25-34) | 76.53 | 81.27 | 11.95 | 47.69 | 95.90 | 103 |
| *Firms' gender culture* | | | | | | |
| Share of firms with hiring pref. for male workers | 47.40 | 47 | 8.77 | 29 | 65 | 103 |
| Share of firms without gender-based hiring pref. | 32.51 | 32 | 6.99 | 16 | 54 | 103 |
| Index of firm's gender culture | 1.19 | 1.13 | 0.42 | 0.54 | 2.45 | 103 |
| *Individuals' gender culture* | | | | | | |
| Children suffer if mother works (score 1-4) | 1.99 | 2 | 0.24 | 1 | 2.5 | 81 |
| Housewife fulfilling as working for pay (score 1-4) | 2.34 | 2.32 | 0.27 | 1.7 | 2.9 | 81 |
| Men more rights to jobs than women (score 1-4) | 1.68 | 1.69 | 0.21 | 1.12 | 2 | 81 |
| Index of individuals' gender culture (score 1-4) | 2.00 | 2 | 0.16 | 1.64 | 2.33 | 81 |
| Ratio of female vs. male literacy rate in 1911, % | 81.65 | 84 | 14.13 | 54 | 101 | 103 |

Notes: The unit of observation is a province (NUTS 3 classification). Labor force participation measures are constructed as averages of years 2004-2007 (data source: *ISTAT*). Measures of firms' gender culture are constructed based on answers to a survey of a nationally representative sample of 100,000 Italian firms in 2003 (*Indagine Excelsior, Unioncamere*). Firms are surveyed about their hiring preferences, including employees' gender. I construct averages, at the province level, for the share of firms with hiring preferences for male workers or the share of firms that are indifferent between hiring female or male workers. The index of firms' gender culture is computed as the ratio between the number of firms that are either indifferent or prefer women to men and the number of firms that prefer men workers. Measures of individuals' gender culture are constructed based on answers to the *World Value Survey (1999)*. The questions are: (i) a pre-school child is more likely to suffer if his or her mother works; (ii) being a housewife is just as fulfilling as working for pay; (iii) when jobs are scarce, men should have more rights than women. For each question and each province, I calculate an average score which increases with a more favorable attitude towards female employment. The index of gender culture is computed as the unweighted average of these three items.

Figure 3: Heatmaps of female labor force participation of young women (25-34)



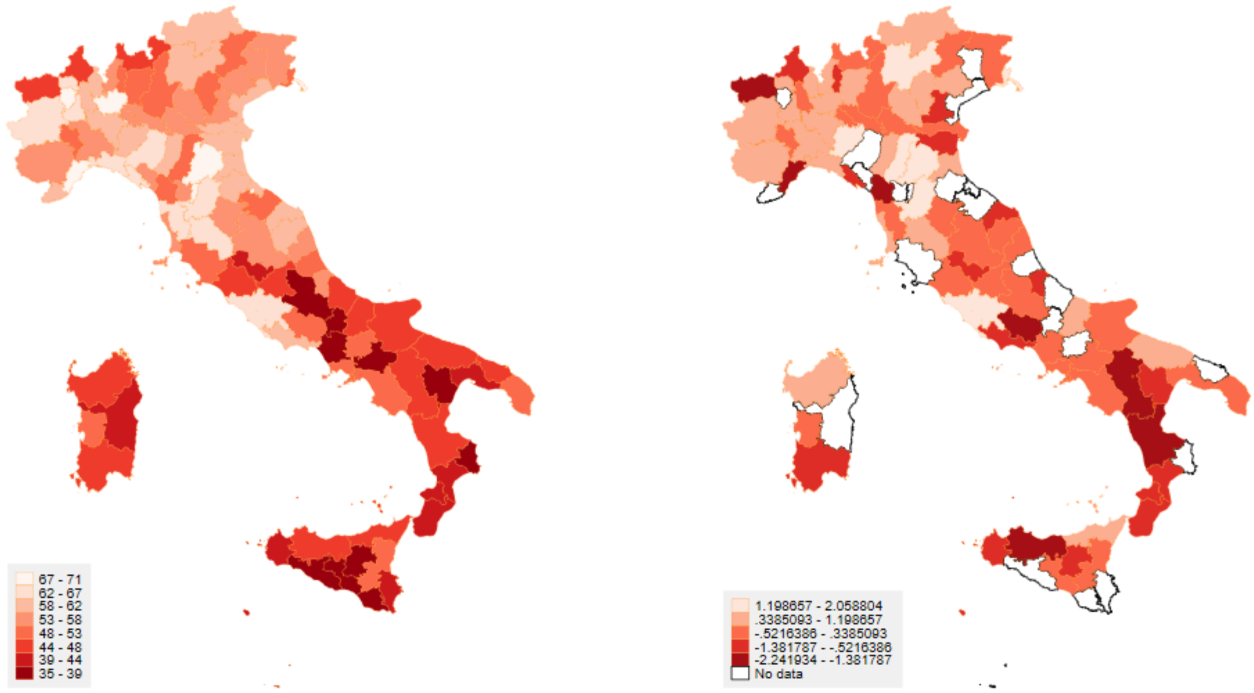

(a) Female LFP (%)




(b) Ratio of female to male LFP (%)

The maps present the female LFP (Panel a) and the ratio of female to male LFP (Panel b) of young women (25-34) in Italy. Each geographical partition is a province (NUTS 3 classification) and there are 103 provinces in total. Both measures are constructed as averages of years 2004-2007.

Figure 4: Heatmaps of gender culture



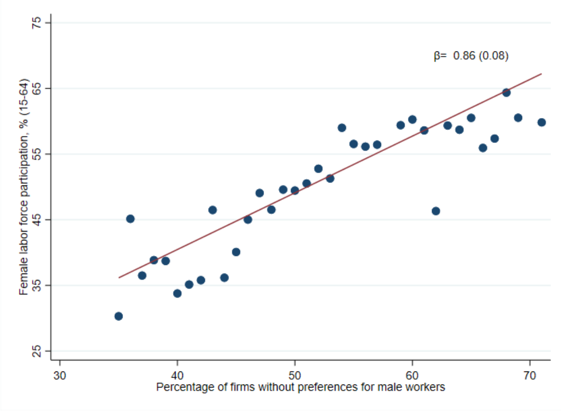

(a) Percentage of firms without preference for male workers

(b) Standardised index of individual gender attitudes

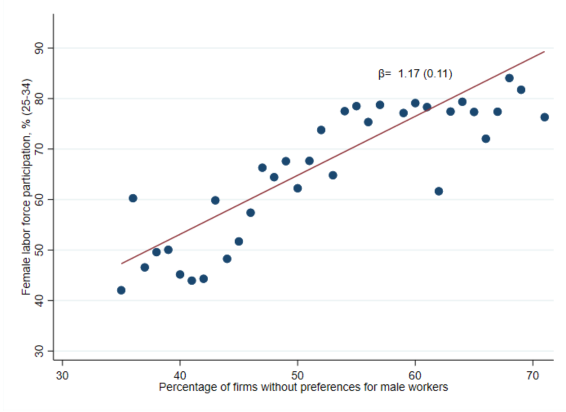
Notes: Panel (a) presents the percentage of firms, within a province, that do not have hiring preferences for male workers. This includes both firms that are indifferent between male and female workers and those that strictly prefer female workers. Panel (b) presents a standardised index of gender culture, based on individual answers to questions related to gender attitudes in the World Value Survey. Each geographical partition is a province (NUTS 3 classification) and there are 103 provinces in total.

Figure 5: Cross-province relationship between FLFP and measures of gender culture

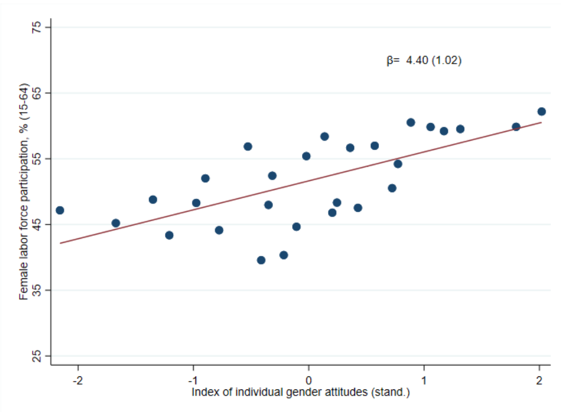
(a) FLFP (15-64) vs. firms' gender culture



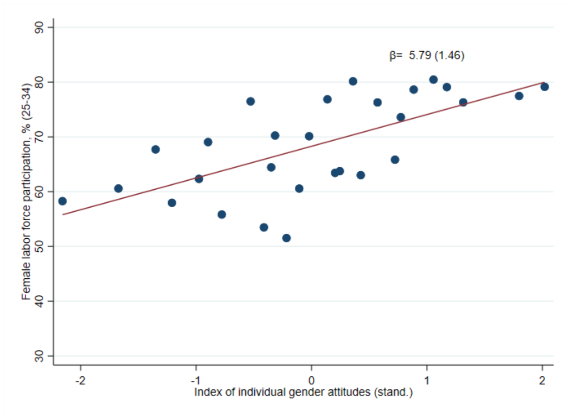

(b) FLFP (25-34) vs. firms' gender culture



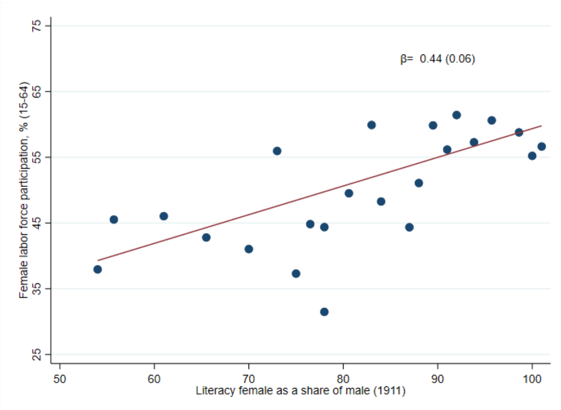

(c) FLFP (15-64) vs. individual gender attitudes



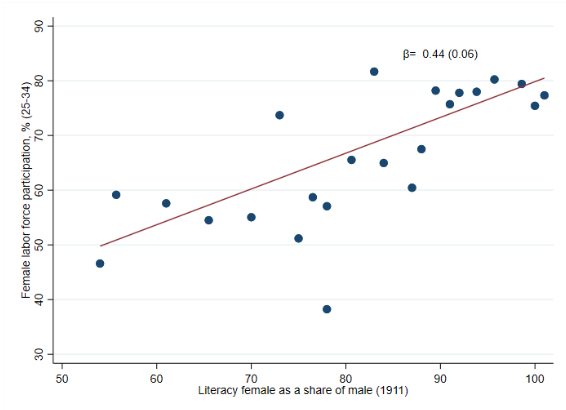

(d) FLFP (25-34) vs. individual gender attitudes




(e) FLFP (25-34) vs. historical gender culture




(f) FLFP (25-34) vs. historical gender culture




Notes: This figure presents binned scatter plots of lagged female labor force participation against alternative measures of gender across provinces. For a description of the variables, refer to Table 1.

Table 2: Summary statistics by response to follow-up survey

| | Respondent | | Non respondent | |
|---|---|---|---|---|
| Variable | Mean | SD | Mean | SD |
| Student characteristics | | | | |
| Female (%) | 57.93 | 49.37 | 57.30 | 49.46 |
| Age at enrollment | 24.33 | 3.93 | 24.61 | 4.23 |
| GPA in Master | 27.64 | 1.58 | 27.54 | 1.65 |
| Graduation grade in Master | 108.21 | 5.82 | 107.72 | 6.20 |
| Mover (changed province to study at Master) % | 57.85 | 49.38 | 56.15 | 49.62 |
| Mover (changed region to study at Master) % | 30.41 | 46.00 | 30.29 | 45.95 |
| FLFP in birth province | 49.53 | 11.20 | 50.10 | 11.02 |
| FLFP/MLFP in birth province | 66.53 | 11.89 | 67.14 | 11.69 |
| Mother: empoyed (%) | 71.84 | 44.97 | 72.06 | 44.89 |
| Mother: managerial occupation (%) | 10.72 | 30.94 | 11.28 | 31.63 |
| Father: managerial occupation (%) | 32.66 | 46.90 | 33.90 | 47.34 |
| Mother: tertiary education (%) | 19.98 | 39.98 | 20.85 | 40.62 |
| Father: tertiary education (%) | 21.31 | 40.95 | 22.67 | 41.87 |
| Low-SES scholarship | 23.59 | 42.46 | 22.55 | 41.79 |
| High-school: liceo | 78.99 | 40.74 | 78.37 | 41.17 |
| Graduation grade in Bachelor | 100.43 | 7.83 | 100.28 | 7.88 |
| Major characteristics | | | | |
| FLFP in prov of university | 53.14 | 10.49 | 53.54 | 10.22 |
| Fulltime employment within major (%) | 72.76 | 23.53 | 72.45 | 23.16 |
| (%) of movers within major | 57.38 | 21.29 | 57.46 | 21.15 |
| (%) of female students within major | 57.68 | 21.69 | 57.97 | 21.77 |
| N | 232,504 | | 83,966 | |

The table presents summary statistics comparing the characteristics of students who responded and those who did not respond to the follow-up survey one year after graduation. Each student is treated as a single unit of observation. These characteristics are observed either in the administrative data or from the institutional survey before graduation. These statistics are based on data from the full sample of female and male students (N=316,470).

Table 3: Summary Statistics - Pre-graduation variables

| | Female (N=69,659) | | Male (N=57,494) | | |
|---|---|---|---|---|---|
| **Variable** | **Mean** | **SD** | **Mean** | **SD** | **p-value** |
| | Aministrative records | | | | |
| Age at enrollment | 24.49 | 4.55 | 24.54 | 4.25 | 0.07 |
| High-school type: liceo | 0.83 | 0.38 | 0.70 | 0.46 | 0.000 |
| GPA in Master degree | 27.73 | 1.49 | 27.29 | 1.66 | 0.000 |
| Final grade in Master degree | 108.48 | 5.53 | 107.09 | 6.26 | 0.000 |
| Duration of studies>min. duration (*fuoricorso*) | 0.33 | 0.47 | 0.39 | 0.49 | 0.000 |
| Move to a different province (NUTS 3) for univ. | 0.59 | 0.49 | 0.56 | 0.50 | 0.000 |
| Move to a different region (NUTS 2) for univ. | 0.30 | 0.46 | 0.28 | 0.45 | 0.000 |
| Female LFP in province of origin | 50.73 | 10.97 | 50.78 | 11.01 | 0.51 |
| Male LFP in province of origin | 74.28 | 4.46 | 74.29 | 4.41 | 0.64 |
| Female LFP in province of studies | 54.05 | 9.99 | 54.21 | 9.96 | 0.005 |
| Male LFP in province of studies | 75.31 | 3.75 | 75.30 | 3.68 | 0.67 |
| | Pre-graduation survey - Family background | | | | |
| Matched to administrative records | 0.92 | 0.27 | 0.91 | 0.29 | 0.000 |
| Financial aid based on family income | 0.24 | 0.43 | 0.21 | 0.41 | 0.000 |
| Mother: university degree | 0.18 | 0.38 | 0.21 | 0.40 | 0.000 |
| Father: university degree | 0.19 | 0.39 | 0.23 | 0.42 | 0.000 |
| Mother: works | 0.73 | 0.44 | 0.73 | 0.44 | 0.016 |
| Mother: executive occupation | 0.06 | 0.24 | 0.07 | 0.25 | 0.000 |
| Father: executive occupation | 0.18 | 0.38 | 0.21 | 0.41 | 0.000 |
| Mother: teacher | 0.13 | 0.34 | 0.15 | 0.35 | 0.000 |
| Father: teacher | 0.03 | 0.18 | 0.04 | 0.19 | 0.000 |
| | Pre-graduation survey - Job-search aspirations | | | | |
| Share attributing high value to: Salary | 0.58 | 0.49 | 0.59 | 0.49 | 0.000 |
| Share attributing high value to: Social utility | 0.38 | 0.49 | 0.28 | 0.45 | 0.000 |
| Share attributing high value to: Hours flexibility | 0.29 | 0.45 | 0.27 | 0.45 | 0.000 |
| Share attributing high value to: Leisure time | 0.31 | 0.46 | 0.29 | 0.45 | 0.000 |

The table reports summary statistics on socio-demographics, academic performance, family background and job-search aspirations, by gender of the student in the sample of analysis. The unit of observation is a student.

Table 4: Summary Statistics - Post-graduation variables

| | Female (N=69,659) | | Male (N=57,494) | | |
|---|---|---|---|---|---|
| **Variable** | **Mean** | **SD** | **Mean** | **SD** | **p-value** |
| | Post-graduation survey: LM outcomes | | | | |
| Response rate | 0.74 | 0.44 | 0.74 | 0.44 | 0.003 |
| Participated in LM | 0.69 | 0.46 | 0.73 | 0.44 | 0.000 |
| Employed during survey | 0.54 | 0.50 | 0.62 | 0.49 | 0.000 |
| Have children | 0.04 | 0.20 | 0.03 | 0.17 | 0.000 |
| Married or live with partner | 0.19 | 0.39 | 0.12 | 0.32 | 0.000 |
| Monthly earnings (€) | 1073.99 | 496.37 | 1320.2 | 507.40 | 0.000 |
| Hourly wage (€) | 8.86 | 6.40 | 8.87 | 5.75 | 0.66 |
| Full-time contract | 0.69 | 0.46 | 0.86 | 0.34 | 0.000 |
| Weekly hours worked | 32.90 | 13.18 | 38.61 | 10.87 | 0.000 |
| Job location different from province of origin | 0.44 | 0.50 | 0.52 | 0.50 | 0.000 |
| Return to province of origin | 0.43 | 0.49 | 0.35 | 0.48 | 0.000 |
| Work abroad | 0.05 | 0.22 | 0.05 | 0.22 | 0.015 |
| Female LFP in province of work | 54.64 | 9.73 | 55.68 | 9.16 | 0.000 |
| Male LFP in province of work | 75.70 | 3.80 | 76.00 | 3.55 | 0.000 |
| High-earnings occupation | 0.58 | 0.49 | 0.78 | 0.41 | 0.000 |
| High full-time occupation | 0.51 | 0.50 | 0.74 | 0.44 | 0.000 |
| High-earnings industry | 0.46 | 0.50 | 0.63 | 0.48 | 0.000 |
| High full-time industry | 0.41 | 0.49 | 0.65 | 0.48 | 0.000 |

The table reports summary statistics on post-graduation outcomes, by gender of the student in the sample of analysis. The unit of observation is a student. The sample of analysis is defined as male and female students who respond to the post-graduation survey, who are employed at the survey date and who have non-missing wages (127,150). The last column reports a p-value on a test of comparison of means between the two groups.

Table 5: The gender earnings gap at labor market entry

| | **Log(monthly earn.)** | **Log(weekly hours)** | **P(Fulltime job)** | **Log(wage)** |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Female | -0.112*** | -0.083*** | -0.051*** | -0.028*** |
| | (0.004) | (0.003) | (0.003) | (0.003) |
| GPA | ✓ | ✓ | ✓ | ✓ |
| Degree FEs | ✓ | ✓ | ✓ | ✓ |
| Cohort FEs | ✓ | ✓ | ✓ | ✓ |
| R-squared | 0.29 | 0.26 | 0.29 | 0.09 |
| N | 127,153 | 127,153 | 127,153 | 127,153 |

Notes: The table reports coefficients from regressions of graduates' labor market outcomes on a female dummy, after controlling for students' GPA, and degree and cohort fixed effects. The sample comprises female and male students who are employed one year after graduation. Standard errors are clustered at the degree level.

Table 6: Sorting into jobs by gender

| | **Log(monthly earn.)** | **Log(weekly hours)** | **High-earn occ.** | **High-earn ind.** |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Female | -0.091*** | -0.058*** | -0.029*** | -0.035*** |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| GPA | ✓ | ✓ | ✓ | ✓ |
| Occupation FEs | ✓ | ✓ | | |
| Industry FEs | ✓ | ✓ | | |
| Province of work | ✓ | ✓ | ✓ | ✓ |
| Degree FEs | ✓ | ✓ | ✓ | ✓ |
| Cohort FEs | ✓ | ✓ | ✓ | ✓ |
| R-squared | 0.37 | 0.41 | 0.49 | 0.34 |
| N | 127,153 | 127,153 | 127,153 | 127,153 |

Notes: The table reports coefficients from regressions of graduates' labor market outcomes on a female dummy, after controlling for students' GPA, and degree and cohort fixed effects. In Columns (1) and (2), additional controls are included for 2-digit occupation and industry fixed effects. The dependent variables in Columns (3) and (4) 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 sample comprises female and male students who are employed one year after graduation. Standard errors are clustered at the degree level.

Table 7: The gender earnings gap excluding individuals with children or married

| | **Log(monthly earn.)** | **Log(weekly hours)** | **P(Fulltime job)** | **Log( wage)** |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Female | -0.104*** | -0.079*** | -0.045*** | -0.03*** |
| | (0.004) | (0.004) | (0.003) | (0.003) |
| GPA | ✓ | ✓ | ✓ | ✓ |
| Degree FEs | ✓ | ✓ | ✓ | ✓ |
| Cohort FEs | ✓ | ✓ | ✓ | ✓ |
| R-squared | 0.31 | 0.27 | 0.31 | 0.10 |
| N | 106,247 | 106,247 | 106,247 | 106,247 |

Notes: The table reports coefficients from regressions of women's labor market outcomes on a female dummy, after controlling for students' GPA, and degree and cohort fixed effects. The sample comprises female and male students who are employed one year after graduation, excluding those with children or who are either married or cohabit with their partners. Standard errors are clustered at the degree level.

Table 8: Estimates of gender culture on women's labor supply one year after graduation

| | **Log(weekly hours)** | | | **Pr(fulltime job)** | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Q4 vs. Q1 of FLFP in birth prov. | 0.072*** | 0.076*** | 0.071*** | 0.025*** | 0.022*** | 0.021*** |
| | (0.011) | (0.011) | (0.012) | (0.008) | (0.008) | (0.008) |
| Province of job FEs | | ✓ | ✓ | | ✓ | ✓ |
| GPA | | | ✓ | | | ✓ |
| Mother's occupation | | | ✓ | | | ✓ |
| Father's occupation | | | ✓ | | | ✓ |
| Cohort | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Degree FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N | 15,838 | 15,835 | 14,600 | 15,838 | 15,835 | 14,600 |

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. The sample comprises female movers who are employed one year after graduation. Standard errors are clustered at the degree level.

Table 9: Characteristics of female movers by gender culture in birth province

| | Movers by quartiles of FLFP in birth prov. | | | Movers by quartiles of FLFP in birth prov. (degree FEs) | | | |
|---|---|---|---|---|---|---|---|
| | Q1 FLFP | Q4 FLFP | Diff. (Q4-Q1) | Q1 FLFP | Q4 FLFP | Diff. (Q4-Q1) | N |
| **Characteristics of students** | | | | | | | |
| Age at enrollment | 24.36 | 24.05 | -0.32*** | 24.13 | 24.28 | 0.16*** | 56,007 |
| GPA during Master (0/30) | 27.66 | 27.91 | 0.25*** | 27.67 | 27.89 | 0.22*** | 56,007 |
| Graduation grade in Master (0-110) | 108.18 | 108.36 | 0.19*** | 107.87 | 108.68 | 0.80*** | 56,007 |
| Graduation grade in Bachelor (0-110) | 100.94 | 101.94 | 1*** | 101.23 | 101.65 | 0.42*** | 50,138 |
| Fraction cohabiting with partner or married | 0.15 | 0.18 | 0.03*** | 0.15 | 0.18 | 0.03*** | 41,681 |
| Fraction with mother with tertiary educ. | 0.18 | 0.19 | 0.01*** | 0.20 | 0.18 | -0.02*** | 51,532 |
| Fraction with father with tertiary educ. | 0.19 | 0.20 | 0.01*** | 0.20 | 0.18 | -0.02*** | 51,532 |
| Fraction with mother in the labor force | 0.60 | 0.84 | 0.24*** | 0.62 | 0.81 | 0.19*** | 50,413 |
| Fraction with father in the labor force | 0.99 | 0.99 | 0.00 | 0.99 | 0.99 | 0.00 | 50,413 |
| Fraction with mother in managerial occ. | 0.08 | 0.12 | 0.04*** | 0.09 | 0.11 | 0.02*** | 50,413 |
| Fraction with father in managerial occ. | 0.27 | 0.34 | 0.07*** | 0.29 | 0.33 | 0.04*** | 50,413 |

Notes: This table provides evidence on the selection of female movers (into educational majors) by province of birth. Movers here are defined as individuals attending university in a different province than where they were born. Each group is divided by the FLFP in their place of birth (top vs bottom quartile of FLFP in Italian provinces). The table compares the ability, socio-demographics and socio-economic background of female movers by place of birth. The left Panel presents raw means by group, while the right panel presents estimates from separate regressions accounting for degree and cohort fixed effects.

Table 10: Estimates of gender culture on men's labor supply one year after graduation

| | **Log(weekly hours)** | | | **Pr(fulltime job)** | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Q4 vs. Q1 of FLFP in birth prov. | 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 | | | ✓ | | | ✓ |
| Cohort | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 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 comprises male movers who are employed one year after graduation. Standard errors are clustered at the degree level.

Table 11: Balancing tests for cohort composition - Female students

| | Student pre-determined characteristics: | | | | | |
|---|---|---|---|---|---|---|
| | **Enroll. age** | **Q4 pre-det GPA** | **Q1 pre-det GPA** | **Mother: college** | **Low-SES grant** | **Mother works** |
| (Mean dep. variable) | (24.33) | (0.24) | (0.23) | (0.19) | (0.24) | (0.72) |
| Avg FLFP in prov of female peers | -0.030 | 0.009 | -0.008 | -0.002 | -0.002 | -0.004 |
| | (0.092) | (0.007) | (0.006) | (0.006) | (0.007) | (0.006) |
| Avg FLFP in prov of male peers | -0.110 | 0.000 | 0.001 | -0.004 | 0.007 | -0.008 |
| | (0.095) | (0.005) | (0.005) | (0.004) | (0.006) | (0.005) |
| Degree FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N degrees | 1,572 | 1,572 | 1,572 | 1,572 | 1,565 | 1,571 |
| Obs | 182,792 | 162,091 | 162,091 | 167,637 | 131,499 | 163,752 |

| | **Mother: HS occ.** | **Mother: teacher** | **Mother: entrepr.** | **Father: HS occ.** | **Father: teacher** | **Father: entrepr.** |
|---|---|---|---|---|---|---|
| (Mean dep. variable) | (0.10) | (0.13) | (0.01) | (0.31) | (0.03) | (0.05) |
| Avg FLFP in prov of female peers | -0.004 | 0.002 | -0.002 | -0.008 | 0.001 | 0.001 |
| | (0.004) | (0.005) | (0.002) | (0.007) | (0.003) | (0.003) |
| Avg FLFP in prov of male peers | -0.002 | -0.001 | 0.001 | 0.001 | -0.001 | 0.001 |
| | (0.004) | (0.004) | (0.001) | (0.005) | (0.002) | (0.002) |
| Degree FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N degrees | 1,571 | 1,571 | 1,571 | 1,571 | 1,571 | 1,571 |
| Obs | 163,752 | 163,752 | 163,752 | 162,734 | 162,734 | 162,734 |

Notes: OLS estimates of the baseline model (equation 1) on the full sample of female students. The dependent variables are predetermined characteristics of the student (indicated in columns). Each regression includes degree (major x university) and cohort FEs. Standard errors clustered at the degree level. Regressors are standardised.

Table 12: Balancing tests for cohort composition - Male students

| | Student pre-determined characteristics: | | | | | |
|---|---|---|---|---|---|---|
| | **Enroll. age** | **Q4 pre-det GPA** | **Q1 pre-det GPA** | **High-school: liceo** | **Low-SES grant** | **Mother works** |
| (Mean dep. variable) | (24.5) | (0.20) | (0.35) | (0.22) | (0.23) | (0.73) |
| Avg FLFP in female peers' provs.: | 0.045 | 0.008 | -0.005 | 0.000 | 0.006 | -0.001 |
| | (0.059) | (0.006) | (0.007) | (0.005) | (0.006) | (0.006) |
| Avg FLFP in male peers' provs.: | -0.070 | -0.003 | 0.000 | -0.005 | 0.002 | 0.009 |
| | (0.074) | (0.006) | (0.007) | (0.006) | (0.007) | (0.006) |
| Degree FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N degrees | 1,572 | 1,570 | 1,570 | 1,570 | 1,564 | |
| Obs | 133,678 | 116,256 | 116,256 | 119,743 | 95,856 | 116,919 |
| | **Mother: HS occ.** | **Mother: teacher** | **Mother: entrepr.** | **Father: HS occ.** | **Father: teacher** | **Father: entrepr.** |
| (Mean dep. variable) | (0.11) | (0.16) | (0.02) | (0.35) | (0.03) | (0.05) |
| Avg FLFP in female peers' provs.: | 0.000 | 0.000 | 0.003 | -0.006 | -0.005 | 0.005 |
| | (0.005) | (0.005) | (0.002) | (0.007) | (0.003) | (0.003) |
| Avg FLFP in male peers' provs.: | -0.001 | -0.001 | 0.001 | 0.014* | 0.001 | 0.001 |
| | (0.005) | (0.005) | (0.002) | (0.007) | (0.003) | (0.003) |
| Degree FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N degrees | 1,570 | 1,570 | 1,570 | 1,570 | 1,570 | 1,570 |
| Obs | 116,919 | 116,919 | 116,919 | 117,049 | 117,049 | 117,049 |

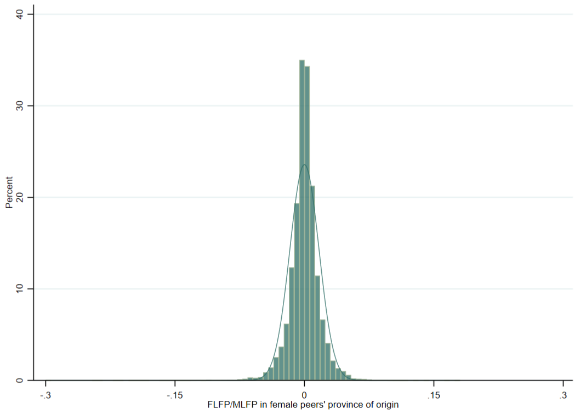
Notes: OLS estimates of the baseline model (equation 2) on the full sample of male students. The dependent variables are predetermined characteristics of the student (indicated in columns). Each regression includes degree (major x university) and cohort FEs. Standard errors clustered at the degree level. Regressors are standardised.

Table 13: F-test: predicting treatment with pre-determined covarites

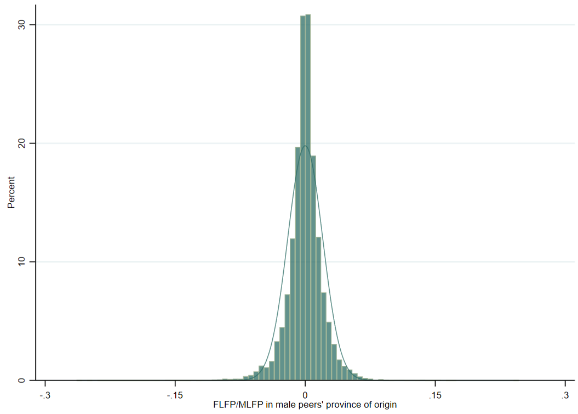
| | (1) Avg FLFP in prov of peers | (2) Avg FLFP/MLFP in prov of peers |
|---|---|---|
| F | 0.80 | 0.75 |
| Prob > F | 0.68 | 0.75 |
| Age at enrollment | ✓ | ✓ |
| Mother's citizenship | ✓ | ✓ |
| Father's citizenship | ✓ | ✓ |
| Mother: college | ✓ | ✓ |
| Father: college | ✓ | ✓ |
| Low-SES scholarship | ✓ | ✓ |
| Mother's occupation FEs | ✓ | ✓ |
| Father's occupation FEs | ✓ | ✓ |
| High-school type | ✓ | ✓ |
| Grade high-school above median | ✓ | ✓ |
| Grade Bachelor above median | ✓ | ✓ |
| Degree FEs | ✓ | ✓ |
| Cohort FEs | ✓ | ✓ |
| N degrees | 1,569 | 1,569 |
| Obs | 211,732 | 211,732 |

Notes: OLS estimates of regressions of treatment (avg FLFP in provinces of peers in (1) and avg FLFP/MLFP in provinces of peers in (2)) on a set of a student's pre-determined covariates. A F-test for the joint significance of regressors is performed. The table reports the value of the F statistic and the corresponding p-value. Regressions are estimated on the full sample of female and male students. Regressions include cohort and degree fixed effects. Standard errors clustered at degree level.

Figure 6: Year-to-Year Variation in Ratio FLFP/MLFP in Peers' Provinces




(a) Female peers




(b) Male peers

Notes: The figure plots the residuals from a regression of the avergage ratio of FLFP to MLFP in peers' provinces of origin, by peers' gender, on degree and cohort FEs. It is plotted against the normal distribution for comparison.

Table 14: Raw and residual variation in peers' culture

| | Mean | SD | Min | Max |
|---|---|---|---|---|
| A: Average FLFP in provinces of female peers | | | | |
| Raw cohort variable | 49.05 | 8.33 | 29.18 | 66.17 |
| Residuals: net of master and cohort FEs | 0.000 | 1.97 | -31.81 | 28.57 |
| | | | | |
| B: Average FLFP in provinces of male peers provinces | | | | |
| Raw cohort variable | 49.10 | 8.45 | 29.18 | 66.17 |
| Residuals: net of master and cohort FEs | 0.000 | 2.1 | -29.45 | 32.09 |

Table 15: Effect of peers on female earnings and labor supply

| | (1) **Log(monthly earnings)** | (2) **Log(weekly hours)** | (3) **P(Fulltime job)** | (4) **Log(hourly wage)** |
|---|---|---|---|---|
| Avg FLFP in prov of female peers | 0.037*** | 0.033*** | 0.019** | 0.003 |
| | (0.013) | (0.012) | (0.009) | (0.012) |
| Avg FLFP in prov of male peers | 0.000 | 0.001 | -0.002 | -0.002 |
| | (0.010) | (0.009) | (0.007) | (0.01) |
| FLFP in own province of origin | ✓ | ✓ | ✓ | ✓ |
| Degree FEs | ✓ | ✓ | ✓ | ✓ |
| Cohort FEs | ✓ | ✓ | ✓ | ✓ |
| R-squared | 0.29 | 0.25 | 0.28 | 0.10 |
| N | 69,645 | 69,645 | 69,645 | 69,645 |

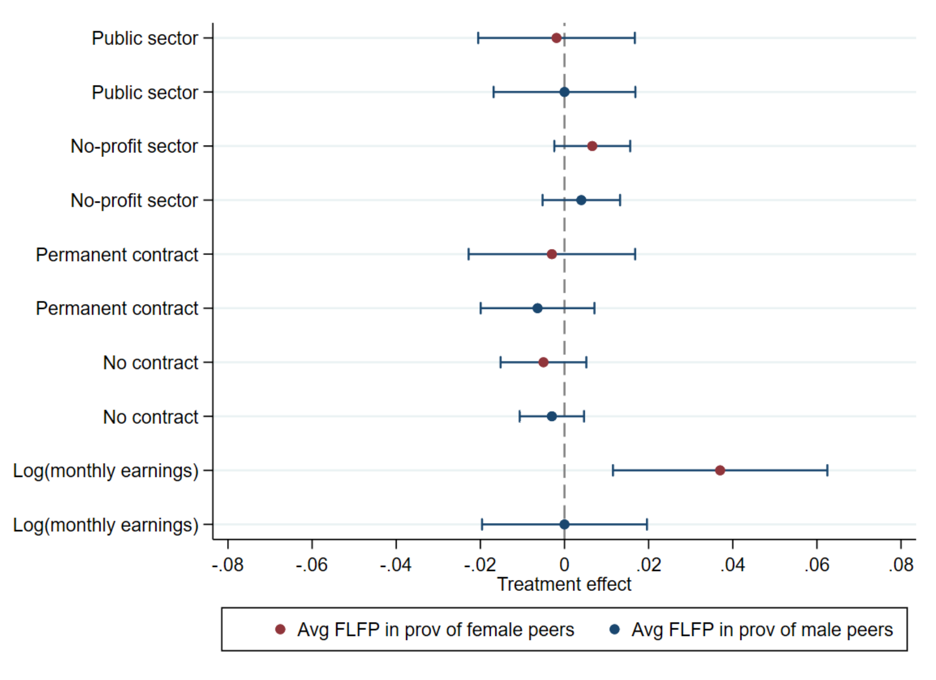
Notes: OLS estimates of a regression of women's earnings and labor supply one year after graduation on: the average FLFP in the provinces of origin of female and male peers and the FLFP in the own province of origin. Regressions include cohort and degree fixed effects. All the estimates are done on the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

Table 16: Effect of peers on occupations and industries

| | Occupation: | | Industry: | | |
|---|---|---|---|---|---|
| | High-earn | High-fulltime | High-earn | High-fulltime | Log(weekly hours) |
| | (1) | (2) | (3) | (4) | (5) |
| Mean FLFP in province of female peers | 0.017* | 0.016* | 0.007 | 0.014 | 0.022* |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.011) |
| Mean FLFP in province of male peers | -0.004 | -0.005 | -0.005 | -0.009 | -0.003 |
| | (0.007) | (0.006) | (0.007) | (0.007) | (0.009) |
| Industry, occupation FEs | | | | | ✓ |
| Province of work FEs | | | | | ✓ |
| FLFP in own province of origin | ✓ | ✓ | ✓ | ✓ | ✓ |
| Degree FEs | ✓ | ✓ | ✓ | ✓ | ✓ |
| Cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ |
| R-squared | 0.39 | 0.47 | 0.34 | 0.38 | 0.38 |
| N | 68,216 | 68,216 | 68,216 | 68,216 | 68,216 |

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 fulltime jobs across occupations and industries, respectively. Specifically, indicators of high-fulltime occupations (industries) are based on whether an occupation (industry) has above-mean shares of fulltime jobs. Regressions include cohort and degree fixed effects. All the estimates are done on the sample of women who are employed one year after graduation. Standard errors clustered at degree level. All regressors are standardised.

Figure 7: Effect of peers on other job characteristics




Notes: The figure presents treatment effects, according to the specification in equation 1, on the other characteristics of women's jobs one year after graduation. Regressions include cohort and degree fixed effects. All the estimates are done on the sample of women who are employed one year after graduation. Standard errors clustered at degree level. All regressors are standardised.

Table 17: Effect of peers on male earnings and labor supply

| | **Log(monthly earn.)** | **Log(weekly hours)** | **P(Fulltime job)** | **Log(wage)** |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Avg FLFP in prov of female peers | 0.013 | -0.000 | -0.001 | 0.014* |
| | (0.008) | (0.008) | (0.006) | (0.008) |
| Avg FLFP in prov of male peers | 0.013 | -0.005 | 0.004 | 0.017* |
| | (0.011) | (0.010) | (0.008) | (0.010) |
| FLFP in own province of origin | ✓ | ✓ | ✓ | ✓ |
| Degree FEs | ✓ | ✓ | ✓ | ✓ |
| Cohort FEs | ✓ | ✓ | ✓ | ✓ |
| R-squared | 0.25 | 0.23 | 0.27 | 0.11 |
| N | 57,476 | 57,476 | 57,476 | 57,476 |

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. Standard errors clustered at degree level. All regressors are standardised.

Table 18: Sensitivity analysis - Female students

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | | By size of degrees | | | | % of students with Bach in same univ | |
| | Benchmark | Exclude small degrees (p5) | Exclude large degrees (p90) | Only large degrees (p90) | Size below mean | Exclude degrees with high share (p90) | Only degrees with low share (p25) |
| Avg FLFP in prov of female peers | 0.037*** | 0.037*** | 0.043*** | 0.005 | 0.050*** | 0.036*** | 0.044** |
| | (0.013) | (0.013) | (0.013) | (0.034) | (0.016) | (0.013) | (0.019) |
| Avg FLFP in prov of male peers | 0.000 | 0.000 | 0.003 | -0.007 | -0.009 | 0.001 | 0.008 |
| | (0.010) | (0.010) | (0.011) | (0.021) | (0.012) | (0.010) | (0.012) |
| Degree FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N degrees | 1,556 | 1,490 | 1,399 | 157 | 1,036 | 1,406 | 392 |
| Obs | 69,645 | 69,222 | 46,518 | 23,127 | 22,797 | 65,319 | 21,767 |

Notes: OLS estimates of the baseline model (equation 1) on log(monthly earnings) for different subsamples. Column (1) refers to the benchmark specification from (equation 1) and also reported in Table 15. Column (2) drops degrees with mean size in the bottom 5% (12 students). Column (3) drops degrees with mean size in the top 10% (more than 89 students). Column (4) refers to the benchmark specification estimated on large degrees (more than 89 students). Column (5) refers to the benchmark specification estimated on degrees with mean size below the mean (45 students). Column (6) drops degrees with high share of students who did the bachelor at the same university (more than 95%). Column (7) refers to the benchmark specification estimated on the sample of degrees with low share of students who did the Bachelor in the same university (below 62%). Regressions include cohort and degree fixed effects. Standard errors clustered at the degree level.

Table 19: Heterogeneity by students' attendance to classes

| | (1) Log(monthly earnings) | (2) Log(weekly hours) |
|---|---|---|
| **A: Students with high attendance** | | |
| Avg FLFP in prov of female peers | 0.047*** | 0.037*** |
| | (0.012) | (0.013) |
| Avg FLFP in prov of male peers | 0.005 | 0.000 |
| | (0.010) | (0.010) |
| **B: Students with low attendance** | | |
| Avg FLFP in prov of female peers | -0.006 | -0.005 |
| | (0.021) | (0.013) |
| Avg FLFP in prov of male peers | 0.007 | 0.009 |
| | (0.020) | (0.017) |
| FLFP in own province of origin | ✓ | ✓ |
| Degree FEs | ✓ | ✓ |
| Cohort FEs | ✓ | ✓ |
| N degrees | 1,552 | 1,552 |
| Obs | 64,135 | 64,135 |
| R-squared | 0.31 | 0.25 |

Notes: OLS estimates of a regression of women's earnings and weekly hours worked 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 interaction terms between the average FLFP in the provinces of origin of female/male peers and an indicator variable for whether the student has low or high attendance to classes. Regressions include cohort and degree fixed effects. All the estimates are done on the sample of women who are employed one year after graduation. Standard errors clustered at degree level. All regressors are standardised.

Table 20: Effect of peers on human capital - Sample of female students

| | GPA | Graduation grade | P(delayed grad.) |
|---|---|---|---|
| | (1) | (2) | (3) |
| Avg FLFP in prov of female peers | 0.047 | 0.071 | 0.006 |
| | (0.029) | (0.102) | (0.008) |
| Avg FLFP in prov of male peers | 0.039 | 0.066 | -0.004 |
| | (0.024) | (0.085) | (0.007) |
| FLFP in own province of origin | ✓ | ✓ | ✓ |
| Degree FEs | ✓ | ✓ | ✓ |
| Cohort FEs | ✓ | ✓ | ✓ |
| Mean dep. variable | 27.78 | 108.61 | 0.30 |
| R-squared | 0.24 | 0.17 | 0.18 |
| N | 182,792 | 182,792 | 182,792 |

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. All the estimates are done on the full sample of women. All regressors are standardised. The dependent variable are not 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 21: Effect of peers on geographic mobility - Sample of female students

| | FLFP prov of work | Reg work = univ | Work abroad | Prov work ≠ birth |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Mean FLFP in province of female peers | 0.155 | 0.012 | 0.004 | 0.007 |
| | (0.151) | (0.011) | (0.005) | (0.010) |
| Mean FLFP in province of male peers | 0.126 | -0.005 | 0.005 | 0.009 |
| | (0.123) | (0.008) | (0.004) | (0.007) |
| FLFP in own province of origin | X | X | X | X |
| Degree FEs | X | X | X | X |
| Cohort FEs | X | X | X | X |
| Mean dependent variable | 54.28 | 0.68 | 0.05 | 0.45 |
| R-squared | 0.59 | 0.15 | 0.07 | 0.18 |
| N | 68,751 | 72,367 | 72,367 | 72,367 |

Notes: OLS estimates of a regression of the geographic mobility decisions of women 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 women who are employed one year after graduation. Standard errors clustered at degree level. All regressors are standardised.

Table 22: Effect of peers on female labor supply, controlling for job location

| | **Log(earnings)** | **Log(weekly hours)** | **P(Fulltime)** |
|---|---|---|---|
| | (1) | (2) | (3) |
| Avg FLFP in prov of female peers | 0.037*** | 0.033*** | 0.019** |
| | (0.012) | (0.012) | (0.009) |
| Avg FLFP in prov of male peers | -0.003 | -0.001 | -0.003 |
| | (0.009) | (0.009) | (0.007) |
| Province of work FEs | ✓ | ✓ | ✓ |
| FLFP in own province of origin | ✓ | ✓ | ✓ |
| Degree FEs | ✓ | ✓ | ✓ |
| Cohort FEs | ✓ | ✓ | ✓ |
| R-squared | 0.34 | 0.26 | 0.30 |
| N | 69,534 | 69,534 | 69,534 |

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, controlling for province of the job fixed effects. Regressions include cohort and degree fixed effects. All the estimates are done on the sample of women who are employed one year after graduation. Standard errors clustered at degree level. All regressors are standardised.

Table 23: Effect of peers on female labor supply, controlling for the share of local students

| | **Log(earnings)** | **Log(weekly hours)** | **P(Fulltime)** |
|---|---|---|---|
| | (1) | (2) | (3) |
| Avg FLFP in prov of female peers | 0.045*** | 0.041*** | 0.022** |
| | (0.013) | (0.012) | (0.010) |
| Avg FLFP in prov of male peers | -0.002 | -0.002 | -0.001 |
| | (0.010) | (0.009) | (0.007) |
| Share of female stayers | ✓ | ✓ | ✓ |
| Share of male stayers | ✓ | ✓ | ✓ |
| FLFP in own province of origin | ✓ | ✓ | ✓ |
| Degree FEs | ✓ | ✓ | ✓ |
| Cohort FEs | ✓ | ✓ | ✓ |
| R-squared | 0.29 | 0.25 | 0.28 |
| N | 69,645 | 69,645 | 69,645 |

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, 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 who are employed one year after graduation. Standard errors clustered at degree level. All regressors are standardised.

Table 24: Effect of peers on women's valuation of job attributes

| | **Index pecuniary** | **Index flexibility** | **Social utility** | **Leisure time** | **Hours flexibility** |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Avg FLFP in prov of female peers | 0.004 | -0.028* | -0.012* | -0.012* | -0.009 |
| | (0.015) | (0.015) | (0.007) | (0.007) | (0.007) |
| Avg FLFP in prov of male peers | 0.002 | 0.006 | 0.001 | 0.001 | -0.004 |
| | (0.011) | (0.011) | (0.005) | (0.005) | (0.005) |
| FLFP in own province of origin | ✓ | ✓ | ✓ | ✓ | ✓ |
| Degree FEs | ✓ | ✓ | ✓ | ✓ | ✓ |
| Cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ |
| Mean dependent variable | 0 | 0 | 0.41 | 0.32 | 0.31 |
| R-squared | 0.09 | 0.04 | 0.09 | 0.03 | 0.04 |
| N | 165,116 | 163,855 | 164,214 | 164,630 | 164,425 |

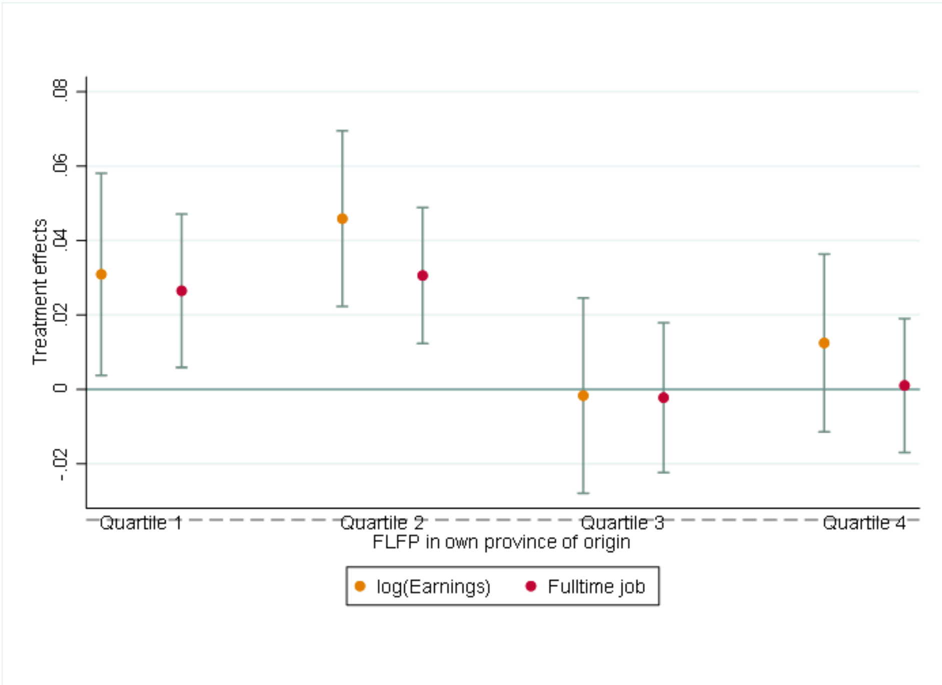
Notes: OLS estimates of regressions of valuation of job attributes on: the average FLFP in the provinces of origin of female and male peers and the FLFP in the own province of origin. The dependent variables in Columns (3)-(5) are indicators of whether a student gives maximum value (i.e. 5/5) to individual job attributes. Answers come the question: "How much do you value attribute X in the job you are searching?" (scale 1-5). The index in Column (1) is constructed by averaging students' rankings of pecuniary job attributes (i.e. salary and career progression). 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 (2) and (2) have been standardised. Regressions include cohort and degree fixed effects. The estimates are done on the sample of women who fill in the institutional pre-graduation survey (92%). Standard errors clustered at degree level. All regressors are standardised.

Table 25: Fields of study

| Variable | Share | N |
|---|---|---|
| Economics and statistics | 0.192 | 92 |
| Humanities | 0.452 | 217 |
| Science and mathematics | 0.204 | 98 |
| Social and political science | 0.152 | 73 |

Notes:

Figure 8: Effects of female peers' culture by quartiles of gender culture in birth province




The figure reports the estimated coefficients of the gender culture of female peers by quartiles gender culture in a woman's own province of origin. These estimates are derived from the empirical model specified in equation (1), where the two peer variables have been interacted with quartiles of FLFP in a student's own province of origin. The model is estimated using data from employed women one year after graduation, and it includes cohort and degree fixed effects. Standard errors are clustered at the degree level.

Table 26: Summary statistics

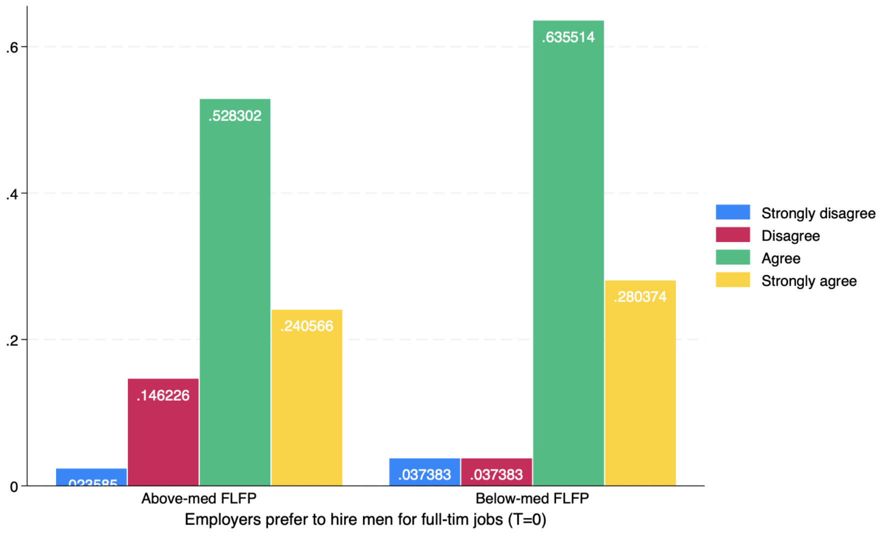
| Variable | Mean | SD | Min | Max | N |
|---|---|---|---|---|---|
| Age | 23.36 | 1.83 | 21 | 39 | 487 |
| Has a partner | 0.464 | | | | 468 |
| Cohabits with partner | 0.056 | | | | 468 |
| If not single, partner is in same major | 0.066 | | | | 243 |
| Father: university | 0.279 | 0.449 | 0 | 1 | 465 |
| Mother: university | 0.314 | 0.465 | 0 | 1 | 468 |
| Share of movers (born in other province) | 0.888 | 0.316 | 0 | 1 | 490 |
| Share of movers (born in other region) | 0.696 | 0.460 | 0 | 1 | 490 |
| FLFP in prov. of origin (all ages) | 54.59 | 11.22 | 29.88 | 66.66 | 489 |
| FLFP/MLFP in prov. of origin (all ages) | 71.53 | 11.99 | 43.62 | 85.69 | 489 |
| FLFP in prov. of origin (ages 25-34) | 71.08 | 14.58 | 38.24 | 86.43 | 489 |
| FLFP/MLFP in prov. of origin (ages 25-34) | 79.10 | 12.55 | 47.69 | 95.90 | 489 |
| Share of firms without pref. for male workers in prov. of origin | 56.05 | 8.38 | 35 | 68 | 464 |

Notes:

1. **Baseline beliefs (T=0)**

| | (1) | (2) | (3) |
|---|---|---|---|
| | Below-med FLFP | Above-med FLFP | Diff (2)-(1) |
| Exp. nb. job offers - 0/10 ($\alpha$) | 3.21 | 3.52 | 0.32 |
| | (0.09) | (0.05) | (0.14) |
| % part-time offers ($\gamma^P$) | 57.64 | 51.19 | -6.45** |
| | (0.90) | (0.45) | (1.34) |
| Acceptance part-time job (%) | 67.43 | 60.39 | -7.04*** |
| | (0.45) | (0.22) | (0.67) |

Figure 9: Perceptions of employers' discrimination by gender culture in birth province



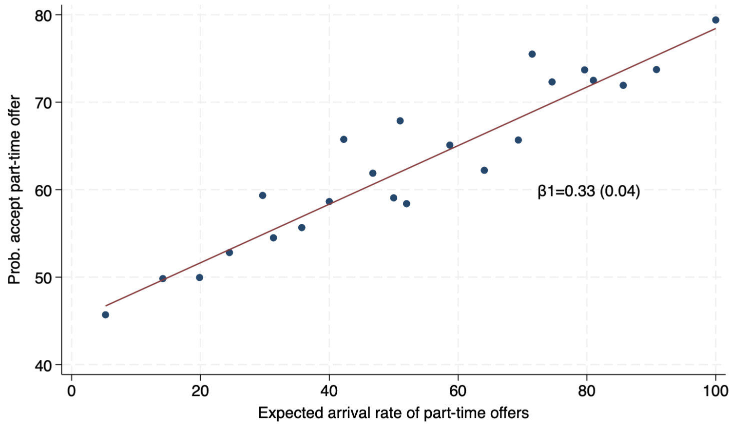

The figure is based on students' answers to the original survey. The sample consists of 490 female students. Students were asked to show their agreement wit the statement "Employers prefer to hire male workers for full-time positions". The figure plots students' answers by gender culture in their province of origin. Beliefs were elicited at the beginning of the first year in the Master (T=0).

2. **Updated beliefs (T=1)**

| | (1) | (2) | (3) |
|---|---|---|---|
| | Below-med FLFP | Above-med FLFP | Diff (2)-(1) |
| Exp. nb. job offers - 0/10 ($\alpha$) | 3.22 | 3.22 | 0.00 |
| | (0.21) | (0.14) | (0.35) |
| % part-time offers ($\gamma^P$) | 52.47 | 50.70 | -1.77 |
| | (1.11) | (0.72) | (1.83) |
| Acceptance part-time job (%) | 62.48 | 62.37 | -0.11 |
| | (0.72) | (0.46) | 1.18 |

Notes: Regressions include field FEs. Standard errors clustered at field level. Panel (1)

Figure 10: Acceptance of part-time jobs and expected arrival rates of part-time jobs




Notes. This figure presents binned scatter plots of the probability of accepting a part-time jobs against the expected arrival rate of part-time jobs. For a description of the variables, refer to Section 10.1.

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