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 know 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 job-search preferences and early-career labor market choices. I exploit unique data covering the universe of college students in Italy and quasi-random variation in peers' culture, based on past female labor force participation in the province of origin. I find that exposure to same-sex peers with more egalitarian gender culture leads women to increase their labor supply. A one standard deviation increase in peers' culture increases female earnings by 3.6%, mostly through higher take-up of full-time jobs. Leveraging information on elicited job-search preferences, I shed light on a novel gender-biased channel: peers shape women's preferences towards relevant job attributes. Peer influence is especially strong in the absence of alternative role models, both in the family and within society. Overall, peers reduce early career gender gaps by 30%. **JEL classification**: J31, J16, J22, R0, Z13.

Keywords: Labor supply, gender gaps, cultural transmission.

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1 Introduction

Social norms are ubiquitous and shape payoffs from many individual decisions. One critical area where they are found to be particularly sticky is in economic decisions of men and women. By prescribing appropriate roles for men and women in society and in the economic sphere, gender norms influence utility derived from several labor market choices (Akerlof and Kranton 2000), leading to large differences in time allocation - e.g. between home and market work - and earnings, among other outcomes[1]. As such, gender norms are usually regarded as obstacles to achieving gender parity in the labor market. Furthermore, the evolution of cultural norms has stalled since the 1990s, and this has coincided with a slowdown in gender convergence (Kleven 2022, Fernandez 2013).

Understanding the mechanisms of cultural change is therefore a significant yet insufficiently understood problem. One hypothesis is that culture evolves through social learning. Existing theories have proposed that intergenerational learning processes feed in cultural change. In the frameworks of Fernandez 2013 and Fogli and Veldkamp 2011, women face uncertainty regarding the costs of working, that they weigh to decide whether to participate in the labor market. Beliefs on these costs are inherited from mothers, and get updated in a Bayesian fashion by observing signals from societal role models, such as the working behavior of women from the previous generation[2]. In these settings, current shocks to labor supply - e.g. such as those driven by technology or changes in wages - fuel cultural change of the next generation through information diffusion.

Besides intergenerational learning channels, other environmental factors could spur social learning. For example, individuals could learn from or imitate the behavior of same-age individuals in their close network. In this article, I provide empirical support to this hypothesis by shedding novel light on cultural assimilation from college peers. The focus is on Italy, a developped country that offers significant spatial variations in gender norms. For example, the percentage of citizens that disagree with the statements "*A woman needs children to be fulfilled*" or "*Men should be given priority when jobs are scarce*" ranges from 35% to 65% across geography (EVS 1990-2008). Similarly, large spatial differences emerge in

[1]See, among others, Kleven 2022, Ichino et al. 2022, Boelman, Raute, and Schönberg 2021, Fernandez and Fogli 2009, Fernandez and Fogli 2006

[2]In Fernandez 2013, women observe noisy signals from the aggregate share of women working. In Fogli and Veldkamp 2011, women observe the behavior of women in their neighborhood.

couples' time allocation, with women spending from 3 to 6 times more hours in home work than their partners (Time Use Survey, 2008). Building upon previous studies, I rely on geographical heterogeneity in past female labor force participation (LFP) as a proxy for cultural norms[3]. Behind is the idea that women who were raised in provinces with low levels of female LFP likely hold different gender identity beliefs than students from high-FLFP areas.

The empirical strategy is to identify the role of peers' culture on women's labor market behavior at the outset of the career. As a thought experiment, think of a world where selection is absent and students from diverse cultural backgrounds are randomised across majors and universities. Focussing on college classmates as a peer group, rather than friends, offers the advantage to overcome issues related to endogeneous peer selection. Moreover, if degrees are sufficiently small in size, students get routinely exposed to the behaviors of all fellow students attending the same degree, with whom they engage in frequent interactions (Mertens et al. 2021). This hypothetical scenario allows to answer the following research question: "Do students assimilate the culture of their peers?"

Features of the Italian context, together with the data structure, allow to approximate this ideal scenario. First, in tandem with gender attitudes, past values of female LFP exhibit substatial spatial variation, ranging from 29% to 66% across provinces. Second, owing to features of the university system, students are highly mobile: 60% of the sample, regardless of the gender, migrate to another province to pursue higher education. As a result, the cultural composition of programs is very heterogeneous. Third, the size of degrees is relatively small, with half counting less than 52 students. Finally, I rely on data covering the universe of college graduates from all fields and universities in Italy. In this database, data from university records are matched to panel survey information on family background, job-search preferences and employment outcomes. Most importantly, these data contain over 1,500 Master degrees observed over multiple enrollment cohorts (2012-2016).

Owing to the data structure, my identification strategy circumvents issues related to the endogeneous selection of students into fields and universities by leveraging quasi-random changes in peers' cultural composition that happen within a given degree - say the Master in Economics at university A - across adjacent cohorts. The identification of peer

[3]The focus is on provinces as geographical partitions (NUTS 3 classification). There are 107 provinces.

effects rests on the assumption that these compositional changes stem from idiosyncratic shocks and not from systematic selection. I provide several exercises to bolster the validity of this approach. Importantly, cross-cohort changes in peers' cultural composition are unrelated to a battery of pre-enrollment student characteristics.

I start by establishing that women's labor market choices, such as their earnings and hours worked, relate to past values of female LFP in their province of origin. Following the epidemiological approach pioneered by Fernandez 2007, I substantiate this claim on the subset of *movers*, defined as students who have migrated to a different province to pursue university. The magnitude of the estimates imply that, when comparing graduates from the same degree, a one standard deviation increase in past female LFP in the province of origin translates into a 2.4% increase in women's earnings. Importantly, the role of culture is not confounded by parental role models, such as mothers' labor supply and socio-economic status, nor by measures of pre-determined ability. Furthermore, it is shown that this relationship is unlikely to be driven by differential selection of movers from different areas.

My main finding is that the exposure to college classmates from provinces with higher female LFP has positive effects on women's labor supply and earnings, above and beyond the role of own culture. The magnitude of this effect is large. A one standard deviation increase in peers' culture increases hours worked by women and the likelihood of full-time jobs by 3% and 2 pps respectively, and leads to a 3.6% increase in monthly earnings. These adjustments happen both within and across occupations. After ranking occupations based on (i) their average earnings or (ii) their share of full-time jobs, my findings indicate that peers also affect women's occupational choices, by leading to higher sorting towards high-paying and long-hours occupations. Instead, they do not influence sorting along other observed margins - such as a firm's industry and mobility decisions - nor they affect fertility decisions.

Leveraging information on elicited job-search preferences, I shed light on a novel mechanism: peers exert an influence on women's preferences for relevant job attributes, as stated during their job search. Specifically, when socialised in cohorts with classmates from high-FLFP provinces, women are found to attribute less importance to specific non-pecuniary job characteristics, such as leisure time, a job's social utility and hours flexibility. These findings can be interpreted as suggestive that changes in aspirations, rather than network effects, could lead to the observed changes in labor market outcomes.

Secondly, my findings shed light on substantial heterogeneity in treatment effects based on the availability of alternative role models, pointing to the existence of cultural substitutability. Peer effects are strongest for women raised in provinces with below-median female LFP and/or grown up in families with scarce maternal role models, such as when the mother is not working. Furthermore, building on the theoretical framework developped in Boucher et al. 2022, I test whether peer effects act through conformism or positive spillovers. A thorough understanding of the mechanisms is in fact necessary to generate implications on the optimal design of peer allocations. I provide evidence of strong asymmetries. While women coming from areas with below-median female LFP react to peer influence, students raised in provinces with female LFP in the top quartile do not assimilate the culture of peers from less egalitarian backgrounds, which supports the spillovers mechanism.

Finally, all of the effects come from female classmates. Being exposed to male peers raised in high-FLFP provinces does not alter women's choices along the observed dimensions. Replicating the analysis on the male subsample shows that men's outcomes do not relate with the female LFP in their province of origin, nor with their peers' culture, regardless of their gender. Because male students are not affected, reduced-form estimates imply that peers can reduce early-career gender gaps by 30%.

This article contributes to several strands of literature. First, it relates to a literature on the role of culture on women's economic decisions. Building on the epidemiological approach of Fernandez 2007, previous studies have documented the role of cultural norms on 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, a few studies have put forward cultural explanations for the persistence of large *child penalties* (Kleven 2022, Cortés et al. 2022, Boelman, Raute, and Schönberg 2021). These studies usually compare choices of immigrants from diverse origins within a host country, relying on cross-country differences to identify the role of cultural traits. Furthermore, they mostly focus on the overall 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 variations in cultural norms based on cross-province differences. I provide novel evidence that culture shape the early-career decisions of female graduates, in a setting where I can rule out many potential confounders.

Second, this paper contributes to the understanding of cultural transmission. Beside theories of intergenerational social learning (Fernandez 2013, Fogli and Veldkamp 2011), we know relatively little on how gender norms evolve and are transmitted. I fill in this gap by providing empirical evidence on cultural assimilation from college peers as a channel of social learning. I show that the environment in which women are socialised in college influences their early-career labor market choices, both through their labor supply and occupational sorting. Previous studies explored horizontal learning from high-school classmates (Olivetti, Patacchini, and Zenou 2020, Mertz, Ronchi, and Salvestrini 2022). Furthermore, my findings indicate the existence of cultural substitutability between peers and alternative role models. With these findings, 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).

Finally, this paper 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 inequality (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.

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 Context:

2.1 Spatial variation in cultural norms:

Previous studies have relied on cross-country variations in female LFP to proxy for differences in cultural norms. In this paper, I focus on Italy, a country that offers substantial variation in attitudes towards gender roles. For example, the share of citizens who disagree with the statements "*A woman needs children to be fulfilled*" or "*Men should be given priority when jobs are scarce*" ranges from 35% to 65% across regions (EVS 1990-2008)[4]. Similarly, women spend from 3 to 6 times more hours in home duties than their male partners based on Time Use data (2008). To approximate for these differences in culture across geography, I rely on variations in local female LFP. This is motivated by empirical evidence showing that gender attitudes and female LFP co-move: in particular, Fernandez 2013 documents a common S-shaped evolution of aggregate labor supply and gender attitudes over a century in the US. According to her theory, women first form their beliefs on the long-run costs of working by observing the share of women from the previous generation working, and then decide whether they participate in the labor market. I show that the empirical relationship between female LFP and gender attitudes is valid in this setting. Figure 3 (Appendix) shows a strong relationship between female LFP and the degree of gender egalitarianism at the local level. 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.

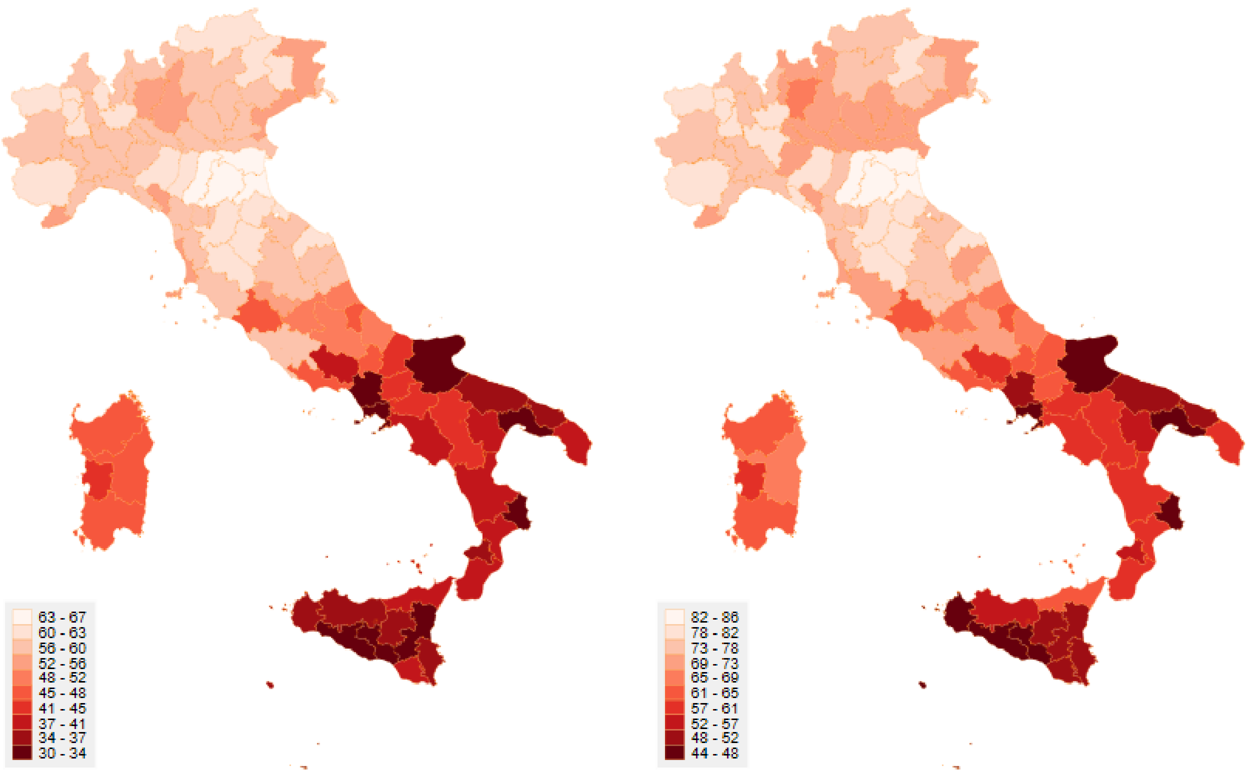
Throughout the paper, I will focus on provinces as a geographical unit. A *province* is an administrative division of intermediate level between a municipality and a region, that corresponds to the NUTS-3 classification[5]. Assignment of students to provinces is based on their province of residence at the enrollmen date, as recorded in university registers. Such province should be interpreted as the area where the student grew up. Two other papers exploit within-country differences in gender norms: Kleven 2022 looks at varia-

[4]Details in ISTAT 2019.

[5]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.

tions across US states, while Boelman, Raute, and Schönberg 2021 exploit cultural divides between East and West Germany. Compared to the two studies, this paper relies on richer and more granular variation from 107 geographical partitions.

Figure 1: Heatmaps of female labor force participation



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

The maps represent female LFP (Panel a) and the ratio of female to male LFP (Panel b) across provinces in Italy. Each geographical partition is a province (NUTS 3 classification) and there are 107 provinces in total. Both measures are averages of the underlying variables over the years 2004-2007. They are calculated on the population in the age group 15-64. Source: Labor Force Survey (Istat).

Figure 1 illustrates large heterogeneity in female LFP across space in Italy. For example, 27% of women participate in the labor market in Barletta (Puglia) against 67% in Bologna (Emilia-Romagna). The mean (standard deviation) of female LFP is 51% (11). Differences are especially salient between Northern and Southern areas. While the variation in female LFP is remarkably large, concerns might arise that such spatial variations reflect labor market conditions rather than cultural norms. To attenuate this concern, I plot in Panel (b) female LFP as a percentage of male LFP. If local labor market conditions were a major driving force, the ratio between female and male LFP should be rather uniformly distributed across space. Instead, we observe almost an identical pattern as the female LFP. In Barletta (Puglia), female LFP is 43% of male LFP against 85% in Bologna (Emilia-Romagna).

2.2 Insitutional background

2.3 Terminology

Throughout the paper, I will use the following terminology: a *degree* is defined as the university program that students choose to enroll at a specific university, e.g. the Master in Economics at the University of Bologna. Therefore, I might refer to degree or master times university fixed effects interchangeably. Since my interest is in the transitions between the education system and the labor market, I only focus on Master students. The majority of undergraduate students, instead, pursue further education. A *university course* is a portion of what is studied in a degree and covers an individual subject, and its unit is one credit (e.g. the course of marketing within a Master in Economics). The *academic curriculum* refers to the prescription of courses and credits that describes a degree.

2.4 Students' mobility

There are 96 universities in Italy, which are rather uniformly distributed across regions. Students can 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[6]. A distinctive feature of this setting is the high degree of spatial mobility of students. In the years 2012-2016, 57% (31%) of students move to another province (region) for college education. Importantly, there are no major differences in mobility between men and women (Table 3). This allows for the composition of degrees to be highly diverse: on average, a university account for 57% of movers, and this share raises to 94% in some (Table 4). All universities have at least some movers (minimum is 12%). Two other features of this setting are particularly valuable: (i) students spend (at least) two entire

[6] Rattini 2022.

years in the same program, and (ii) the size of Master degrees is relatively small. Indeed, 50% of degrees count less than 57 students and 25% comprise less than 32 students. Due to relatively small sizes, it is likely that every individual in a cohort can act as role models for the others.

3 Data and Sample Construction

The empirical analysis relies on unique data covering (almost) the universe of college graduates from all fields of study in Italy (source: AlmaLaurea). Specifically, 71 universities participated in this data collection between 2012 and 2016, representing 92% of the population of university students in Italy (as of 2016). A salient feature of this dataset is its comprehensiveness, if compared to other traditional data sources. This database matches administrative data from university records with detailed survey data coming both from a pre-graduation compulsory survey (response rate: 100%) and from multiple post-graduation surveys. Details on the three sources are listed herafter:

1. **Administrative records** collect information on academic achievements (GPA, final grade, numbers of exams passed), students' socio-demographics, enrollment and graduation dates and unique identifiers of degrees. Importantly, I rely on administrative data to identify college peers and their characteristics of interest. This ensures that all peers are observed.

2. **Pre-graduation survey** that students fill in after completion of their academic curriculum and few days before graduation. Since the survey is compulsory, the response rate is exceptionally high and close to 100%. The survey collects detailed information on students' job-search intentions, including their desired job's characteristics and their valuation of several job attributes. This survey also contains rich information on parental background, such the occupations of both parents and their education level.

3. **Post-graduation survey** after one year from graduation: collect information on job characteristics - such as wage, hours worked, full-time, industry, occupation, location - as well as retrospective information on the job-search process. The response rate is 74%.

I use data on multiple cohorts of students (2012-2016), who graduate between 2014 and 2021. Because the majority of undergraduate students pursue further education, I restrict the sample to master students, who usually transition to the labor market. Note that data are collected on cohorts of graduates. Based on administrative data on exact enrollment and graduation dates, as well as unique degree identifiers, I reconstruct enrollment cohorts. I define as peers all students who enroll in the same degree in the same academic year, according to university records[7]. In the final sample, I consider an unbalanced panel of degrees that exist for at least 3 consecutive years and that count at least 2 women and 2 men in the same cohort. These two restrictions eliminate around 3% of the original sample. The final sample is composed of 316,463 students from 1,572 degrees and 71 universities. Note that the causal analysis of peers on labor market choices will be conducted on the subset of students who respond to the survey and are employed after one year from graduation. These students do not differ substantially from those who do not respond or are not employed based on observables (Table 5). Distributions of students across fields of study and universities are shown in Table 1 and 2. Summary statistics by gender are shown in Table 6 and 7.

4 Gender gaps in earnings and labor supply

4.1 Empirical facts

In accordance with previous findings (Cortes, Pilossoph, et al. 2022, Bertrand, Goldin, and Katz 2010), labor market outcomes of male and female graduates diverge soon in the career. Table 8 reports the coefficients from separate regressions of (i) log(monthly earnings), (ii) log(weekly hours worked) and (iii) a full-time indicator on a female dummy, after removing degree and cohort fixed effects. These regressions are estimated on the sample of male and female students who who answer to the post-graduation survey after one year from degree completion (74%) and who are employed when the survey is conducted (57%)[8]. Note that an equal share of men and women respond to the survey (Table

[7] A drawback is that I lose track of students who drop out, which account for around 15% (source: Ministry of Education).

[8] Note that this share excludes students who are in internship or in specific apprenticeship programs.

7). Gender differences in the probability of being employed after one year relate to sorting across fields of study and disappear once I remove degree fixed effects. Results indicate that the gap in earnings is large already at the outset of the career. Female graduates earn 11% less than their male peers graduating from the same degree (Column 1), in line with previous findings on MBA students in the US (Bertrand, Goldin, and Katz 2010). This gap does not reflect gender differences in academic performance (Column 2), as measured by students' GPA and alternative proxies. Instead, differences in weekly hours worked largely contribute. The earnings gap is reduced to 6% when adding controls for weekly hours worked and a full-time indicator (Column 3). Female graduates sort towards jobs with fewer hours (-8%) and are 5 percentage point less likely to hold a full-time contract, conditional on identical educational choices (Columns 5 and 7). Such differences in hours worked do not reflect sorting across industries and occupations (Appendix). In addition, while I report results at the mean, these patterns are consistent across fields of study, albeit with heterogeneous magnitudes. These findings offer novel comprehensive evidence on the existence of systematic gender differences in labor supply among the high-skilled population in Italy.

4.2 Fertility

The literature on *child penalties* (Kleven 2022, Kleven, Landais, and Søgaard 2019, Bertrand, Goldin, and Katz 2010) would interpret such differences in labor supply as the consequence of mothermood. However, only a small fraction of women in the sample have children (4%) and results persist when I remove those from the sample. While realised fertility is not yet at play, I cannot rule out that women invest less in their early career in anticipation of fertility in the near future. Anticipation of fertility could be a plausible driver, especially in light of the evidence on high employment costs of motherhood in Italy (Casarico and Lattanzio 2022). However, this hypothesis find little empirical support, since the fraction of women with children remains below 10% in the first five years from degree completion and the share of women who declare to be in couple one year after degree completion is relatively low (18%). Moreover, that women correctly anticipate their future labor market outcomes has found limited empirical support. Rather, women significantly underestimate the employment costs of motherhood (Kuziemko et al. 2018.

Previous research on college graduates at Bocconi university also indicate that students significantly underestimate future gender wage gaps (Filippin and Ichino 2005).

4.3 Epidemiological approach: Italian movers

Movers are defined as Italian-born individuals, who move to a different province, than the one of residence, to pursue college studies. This builds on the epidemiological approach pioneered inn Fernandez 2007, that usually focus on immigrants within a host country rather than within-country movers. Approach similar to Kleven 2022

4.4 Gender gaps and peers' culture

In the next of the analysis, I will investigate the role of college peers as a driver of women initial labor market choices. Before dwelving in the causal analysis, Figure 2 plots women's outcomes against peers' culture, measured by past female LFP in peers' provinces of origin. Both eaenings and hours worked exhibits a strong upward relationship with this measure of peers' culture. Interestinngly, gender gaps along these two dimensions shrinks with increases in peers' culture. This descriptive fact motivates the rest of the analysis.

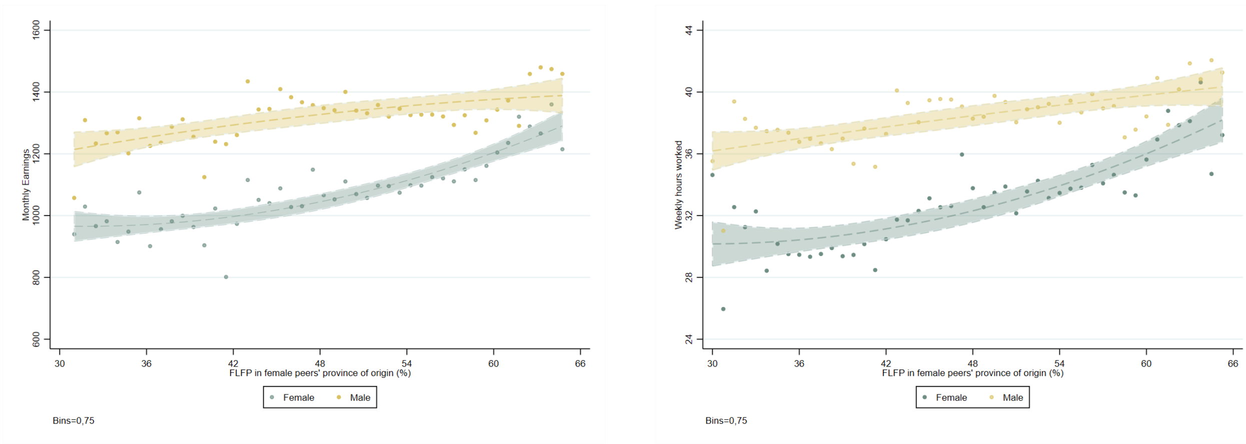
5 Identification Strategy and Empirical Model

The main threat to the identification of peer effects in this context relates to *selection*, or endogeneous peer formation, which arises because students self-select into degrees and universities and, hence, into peer groups (Hoxby 2000). As a consequence, students might be exposed to peers with more or less conservative culture in a way that is correlated with their unobserved characteristics or measures of school's quality that are likely to affect their success in the labor market. 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 exploiting the variation in peers' geographical origins that takes place within the same degree across adjacent cohorts[9]. I can implement this identification strategy due the structure of the data, which covers 1,572 master degrees and multiple

[9] This approach has been previously adopted in the peer effects literature (e.g. Olivetti, Patacchini, and Zenou 2020, Carrell, Hoekstra, and Kuka 2018)

Figure 2: Earnings and hours worked across female peers' culture

(a) Monthly earnings (b) Weekly hours worked



Notes: These figures plot monthly earnings (Panel a) and weekly hours worked (Panel b) as a function of female peers' culture, as proxied by past female LFP in the province of origin. In Panel a, each dot represent mean earnings by bins of FLFP/MLFP in female peers' province of origin. In Panel b, each dot represent mean hours worked by bins of FLFP/MLFP in female peers' province of origin. The size of each bin is 0.85 percentage points. The sample of women (men) consist of 69,644 (57,474) units.

cohorts (2012-2016).

Therefore, my 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 Y_{idc} is the outcome of student *i* in master *d* and cohort *c*. The main labor market outcomes of interest are weekly hours worked, monthly earnings, a full-time job indicator and the propensity to be employed in high-earnings or full-time intensive occupations. I estimate the empirical model on the two subsamples of female and male students separately and I allow for gender-specific peer effects. This reflects the idea that the gender composition of an individual's networks potentially affects the type of information received, as shown in previous work (Currarini, Jackson, and Pin 2009). In the subsample of women, the treatment variables of interest are $\overline{FLFP}^{FP}_{-i,mc}$ and $\overline{FLFP}^{MP}_{i,mc}$, i.e. the mean past female LFP in the province of origin of female peers and of male peers respectively. They 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:

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

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

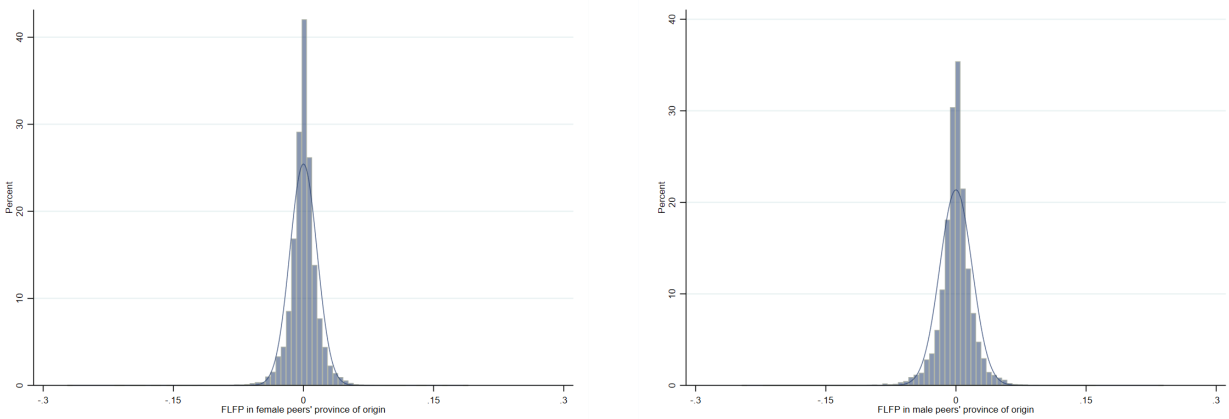
Note that the leave-one-out strategy induces a mechanical negative correlation between female LFP in the own province of origin and the average across same-sex peers. As an example, consider two female students in the same degree and cohort: if one comes from a city where 30% of women participate in the labor market against 60% in the province of origin of the other student, the first will be exposed to higher mean FLFP across female peers than the second by construction, conditional on being exposed to the same peers. To account for this, I also control for $FLFP_{idc}$ in the regression.

Degree fixed effects θ_d capture unobserved differences in students' characteristics among degrees and universities or time-invariant features of degrees, such as their quality. Cohort fixed effects α_c capture common (economic) shocks that affect labor market outcomes of all students from a given enrollment 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.

5.1 Support to the identification strategy

In order for this strategy to uncover causal effects, one needs that the cross-cohort variation in peers' geographical composition within degrees results from random fluctuations rather than from systematic selection. In other terms, while students can self-select into degrees and universities based on their average composition, they should not anticipate the idiosyncratic composition of their specific cohort. Through a vast array of balancing tests, I show that this assumption is credible. Specifically, I test that the cross-cohort variation in the average female LFP across peers' provinces is not correlated with predetermined individual characteristics. Table 9 reports the coefficients from separate regressions of individual characteristics - e.g. performance in previous education, age at enrollment, etc - on the mean female LFP in peers' provinces, after controlling for the FLFP in their own province of origin and removing degree and cohort fixed effects. None of the estimated correlations appear to be significantly different from zero, which alleviates the concern of systematic sorting on the basis of observable characteristics. Additional balancing tests are shown in Table 10, that reports the coefficients from regressions of average peers characteristics on the female LFP in own province of origin. As a further randomization check, I inspect whether the variation in the mean FLFP in peers' provinces of origin is *as good as random*. Figure 3 plots the mean female LFP in peers' provinces - separately for female peers (Panel a) and male peers (Panel b) - after removing degree and cohort fixed effects. The cross-cohort variation in peers' geographical composition ressembles a normal distribution, which adds credibility to the identifying assumption. Finally, the im-

Figure 3: Year-to-Year Variation in the mean female LFP in Peers' Provinces



(a) Female peers

(b) Male peers

Notes: The figure plots residuals from a regression of average female LFP in peers' provinces of origin on degree and cohort FEs. It is plotted together with the normal distribution for comparison.

plementation of this empirical approach requires that there is sufficient residual variation in peers' geographical origins after netting out degree and cohort fixed effects. Table 11 provides evidence supporting this requirement. Removing degree and cohort fixed effects reduces variation in the mean FLFP across female peers (Panel A) from 8.14 percent to 1.6 percent and the one across male peers from 8.16 to 1.84 (Panel B). Between 20% and 23% of the original variation is left unexplained: I will rely on this residual variation to estimate the effects of peers' culture on female outcomes.

6 Main Results

Earnings and Labor Supply. Results from the estimation of the empirical model in (1) on the subsample of female students are presented in Table 13. I consider, as dependent variables, monthly earnings and weekly hours worked, both in logarithmic forms, and a full-time job indicator. All specifications include degree and cohort fixed effects and standard errors are clustered at the degree level[10]. Results indicate that women's labor supply and earnings are related to the female LFP in their province of origin (Columns 1 and 4). The magnitude of this estimate imply that women who were raised in provinces with higher female LFP earn 1.9% (for each stanard deviation increase) more each month than their college classmates raised in provinces with lower female LFP. Most importantly, exposure to same-sex peers from areas with high female LFP affects women's labor supply, by inducing a higher take-up of full-time jobs and an increase in hours worked (Columns 4 and 5). The magnitude of this effect is large: a one standard deviation increase in peers' culture ($\Delta\overline{FLFP}^{FP}_{-i,dc}$ =8.14 percentage points) increases hours worked by 3% and the incidence of full-time jobs by 2 percentage points (3% relative to the mean). This results into a 3.6% increase in monthly earnings (Column 1). Controlling for academic performance does not alter the estimated effects (Column 2), which excludes that the latter acts as a mediating channel. These adjustments along the intensive margin of labor supply take place both within and across occupations.

Occupational sorting and fertility. In table 14, I estimate the empirical model in (1) using as dependent variables indicators for jobs in high-wage or full-time intensive occupations and industries. To construct such indicators, occupations and industries are ranked based

[10] I propose alternative clustering in the robustness exercises, such as at the university level or at the province of origin level, and I show that they do not alter the statistical conclusions.

on (i) their average earnings or (ii) their share of full-time jobs. One occupation (or industry) is defined as high-wage (or full-time intensive) if its average salary (share of full-time jobs) lies above the median of the afore-mentioned distribution. According to these estimates, college classmates from more egalitarian provinces influence female occupational choices, by leading to higher sorting towards occupations with higher earnings and incidence of full-time jobs. When exposed to female classmates from areas with high female LFP, the likelihood of choosing a high-earnings occupation increases by 2.4 pps., which represents a $4,3\%$ increase relative to the mean. Peers do not affect other observed job's characteristics, such as the firm's industry and mobility decisions. Furthermore, there is no evidence of peer effects on fertility decisions (Column 5).

Gendered peer effects. Evidence from Table 13 and Table 14 show that peer influence change women's labor market coices and that the effect comes entirely from other female classmates. Being exposed to male peers raised in more egalitarian provinces do not alter women's choices, along any of the observed dimensions. This is likely to arise if female LFP in the place of origin is a poor proxy for men's working culture, i.e. if men raised in areas with more egalitarian gender attitudes do not differ in their labor market behavior from those raised in less egalitarian places. If this happens, cultural assimilation from male peers would hardly materialize. Results in Table 15 provide empirical support to this hypothesis. Here, I replicate the empirical model in (1) on the subsample of male students. Labor market outcomes of male students exhibit little or no relationship with the female LFP in their province of origin, which rationalizes the absence of an effect from male peers on women's outcomes. Moreover, their labor market choices are not affected by changes in their peers' geographical compositions, regardless of their classmates' gender. Another explanation for the presence of same-sex peer effects - which would have been more relevant were local female LFP a better suited proxy for male working culture - relates to homophily and gender segregation (Currarini, Jackson, and Pin 2009). For example, if students establish closer networks with other students of the same gender, cultural assimilation would be stronger from same-gender peers. Mertz, Ronchi, and Salvestrini 2022 provide empirical support to this hypothesis in the context of high-school students in Denmark.

6.1 Mechanisms

Why do peers change women's labor market choices? Alternative non-exclusive mechanisms could lead to the observed changes in women's labor supply. For example, peers could foster social learning, e.g. by providing information on broader sets of jobs; alternatively, they might serve as a network or as a mean of cultural assimilation. In the latter case, female students would assimilate their peers' culture if the cost of deviating from the prevailing norm is high, or if peers act as role models and shape gender identity beliefs. Under both circumstances, we expect peers to influence women's preferences for jobs, which would lead to changes in their career choices. I test this channel leveraging data on elicited preferences for job attributes. In the pre-graduation survey, students rank their preferred job characteristics by answering to the question "How much do you value *X* in the job you are searching?" (scale 0-5). X is a vector of pecuniary and non-pecuniary job attributes. I focus on a subset of relevant job attributes: social utility, leisure time and hours flexibility. The empirical evidence indicate that women who give high value to these factors are found to work shorter hours one year later. Based on students' rankings of these items, I construct indicator variables for whether a student attributes maximum value (5/5) to separate job attributes. I estimate the empirical model in (1) using such indicator variables as dependent variables (Tablle 16). When exposed to a cohort with more female peers from high-FLFP provinces, women decrease the importance they give to non-pecuniary job attributes, in particular to leisure time and the job's social utility. These findings are consistent with a change in aspirations leading to the observed changes in labor market choices.

7 Robustness analysis

I corroborate my findings on the subsample of female students by performing a set of robustness checks (Table 15). Peer effects are robust to the inclusion of controls for parents' occupation and education, and when controlling for the share of peers with working mothers and the share of students with mothers in executive roles. In addition, I provide evidence that results are not driven by the share of high-achieving peers (based on performance in previous education).

8 Non-linearities and asymmetric peer effects

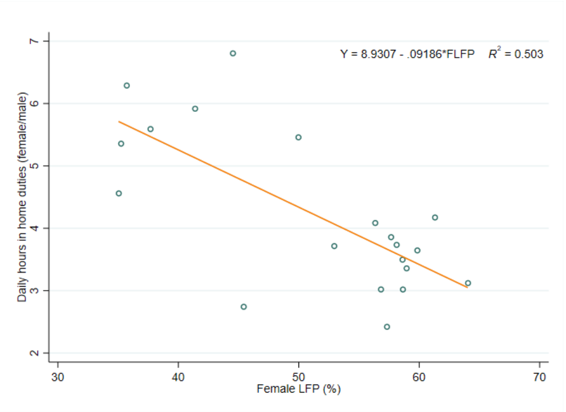
So far, I have relied on a linear-in-means model to uncover the average peer effect, hereby assuming that individuals are linearly affected by the mean culture of their peers. However, this hypothesis is too restrictive in many real-life situations. Rather, non-linearities in the effect of peers can arise under specific behavioural foundations. Building on the theoretical framework developped in Boucher et al. 2022, I test two alternative mechanisms for peer influence: conformism and spillovers. Under the former, agents bear a cost from deviating from their peers' actions and act to minimise the distance between their action and the social norm. In such a context, some agents will provide positive externalities to their peers, if their action is above the social norm, while others provide negative externalities, if their action is below the social norm. Under the spillovers scenario, agents are positively affected by the spillovers that they receive from their peers: this could happen if a group of peers acts as a role model. Discerning between the two channels is important, as it yields significant implications for the optimal allocation of peers. I therefore explore the dynamics of cultural assimilation in this setting, by shedding new light on substantial heterogeneity in treatment effects based on the availability of alternative role models. Table 19 reports coefficients from regressions of log(earnings) on the share of peers from provinces in the bottom and top quartile of the distribution of FLFP interacted with quartiles of FLFP in the own province of origin. Results provide evidence of substantial asymmetries in peer influence: increasing the share of peers from areas with very low FLFP (bottom quartile), while leaving the share of those in the top quartile fixed, negatively affects the earnings of women who are coming from places with below-median FLFP, without affecting earnings of women from areas with higher FLFP.

9 Conclusions

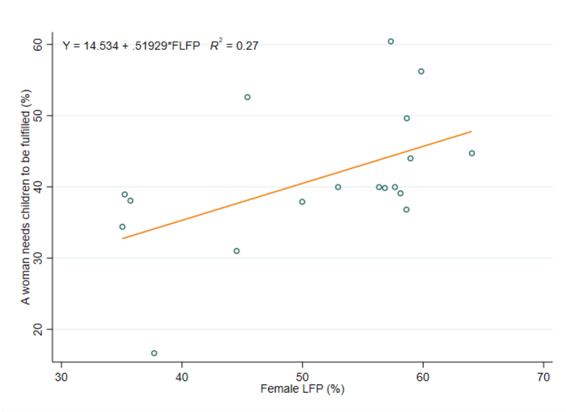
Gender differences in earnings and labor supply are pervasive across labor markets, industries and occupations. These reflect in large part differential sorting of men and women towards jobs and firms. Using data on the universe of college graduates in Italy, I document the existence of a large gap in 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. In particular, net of degree fixed effects, women are more likely employed under part-time contracts 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-pay jobs is related to the culture prevailing in their province of origin, as proxied by past values of female LFP. Consistent with the epidemiological literature, this relationship holds for *movers*, i.e. students who migrate to a different province. 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 decisions. Leveraging extensive data on 1,572 Master degrees in Italy (2012-2016), my identification strategy exploits quasi-random changes in peers' cultural composition that take place within a degree across adjacent cohorts. My findings indicate that exposure to peers with more egalitarian gender culture affects women's career choices. c along the occupational margin. 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 leisure time and the job's social utility. I find evidence of strong asymmetries in peer influence. Peer influence is especially strong towards women who lack alternative role models: 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 the spillovers mechanism. These results yield important implications on gender inequalities: because male students are not affected by peer influence, peers help reduce early-career gender gaps by 30%.

APPENDIX

Figure 4: Correlation between female LFP and cultural norms



(a) Time in home duties (female/male)



(b) Women need children to be fulfilled

Panel (a) represents daily hours devoted to home duties, as a ratio of female to male, regressed on female LFP. The geographical unit of analysis is the region (NUTS 2). The indicator of time spent on family duties is constructed on couples where both partners work. The indicator of time spent on home duties come from the Italian Time Use Survey (2008). Panel (b) represents the percentage of individuals that disagree with the statement: "A woman needs children to be fulfilled", regressed on female LFP. Elicited gender norms come from the European Value Survey (1990, 1999, 2008). In both panels, each point corresponds to a region (NUTS 2). Female LFP is the average over the 2004-2007 period. Source: calculations based on time use and LFS data (Istat) and on EVS (1990, 1999, 2008).

Table 1: Fields of study - Sample of Analysis

Field of study	N	Percent
Business, economics and statistics	29,567	23.25
Engineering	27,115	21.33
Social and political sciences	11,545	9.08
Humanities	10,256	8.07
Modern languages	7,727	6.08
Psychology	7,047	5.54
Biology	6,225	4.90
Medical sciences	5,567	4.38
Architecture	5,354	4.21
Sport	4,372	3.44
Maths and Physics	4,064	3.20
Pedagogy	3,469	2.73
Agriculture	3,014	2.37
Chemistry-Pharmacy	1,625	1.28
Security and defense	203	0.16

Notes: The sample includes male and female students who answer to the survey one year after degree's completion, who work when the survey is conducted and who have non-missing wages (127,150).

Table 2: List of universities - Sample of Analysis

University	N	Percent	University	N	Percent
Bologna	10,667	8.39	Torino Politecnico	6,922	5.44
Padova	6,390	5.03	Catania	1,955	1.54
Roma Sapienza	8,703	6.84	Parma	2,531	1.99
Firenze	3,624	2.85	Venezia IUAV	1,096	0.86
Torino	6,811	5.36	Bari	1,881	1.48
Napoli Federico II	6,086	4.79	Venezia Ca' Foscari	3,584	2.82
Milano	5,877	4.62	Roma Tre	3,077	2.42
Palermo	2,320	1.82	Foggia	389	0.31
Pisa	2,876	2.26	Milano Bicocca	3,600	2.83
Modena e Reggio Emilia	2,670	2.10	Catanzaro	119	0.09
Roma Tor Vergata	3,175	2.50	Piemonte Orientale	589	0.46
Genova	2,891	2.27	Napoli Benincasa	279	0.22
Pavia	2,196	1.73	LUM Jean Monnet	117	0.09
Marche Politecnica	1,904	1.50	Siena	1,254	0.99
Cagliari	1,026	0.81	Trieste	1,142	0.90
Calabria	1,401	1.10	Trieste	1,142	0.90
Camerino	242	0.19	Udine	1,200	0.94
Cassino e Lazio Meridionale	427	0.34	Tuscia	475	0.37
Enna Kore	216	0.17	LIUC Carlo Cattaneo	797	0.63
Ferrara	872	0.69	Basilicata	146	0.11
Salento	1,147	0.90	Milano Vita-Salute S. Raffaele	168	0.13
Macerata	699	0.55	Siena Stranieri	82	0.06
Messina	926	0.73	Bolzano	99	0.08
Milano IULM	692	0.54	Roma Foro Italico	422	0.33
Perugia	1,566	1.23	Roma Campus Bio-Medico	264	0.21
Salerno	1,659	1.30	Roma UNINT	513	0.40
Sassari	391	0.31	Scienze Gastronomiche	54	0.04
Molise	242	0.19	Insubria	304	0.24
Verona	2,158	1.70	Sannio	359	0.28
Napoli Parthenope	941	0.74	Teramo	257	0.20

Napoli L'Orientale	704	0.55	Perugia Stranieri	125	0.10
Brescia	1,035	0.81	Urbino Carlo Bo	1,130	0.89
Reggio Calabria Mediterranea	279	0.22	Trento	1,875	1.47
Bari Politecnico	1,028	0.81	Roma LUMSA	417	0.33
Campania Luigi Vanvitelli	1,481	1.16	Bergamo	1,654	1.30
Chieti e Pescara	1,732	1.36	L'Aquila	1,220	0.96

Notes: The table reports the list of universities that participate in the data collection (71 during the years of this analysis). The distribution refer to the students who are part of the sample of analysis. The sample consider male and female students who answer to the survey one year after degree's completion, who work when the survey is conducted and who have non-missing wages (127,150).

Table 3: Mobility - All students

Variable:	Female	Male
Move to a different province (%)	57.8%	57.2%
Move to a different region (%)	29.5%	31%

Notes: These statistics are calculated on the total of students who enroll in a master degree in one of the 71 universities participating in the data collection (N=316,463).

Table 4: Percent of movers within universities

25th percentile	median	mean	75th percentile
39.9	59.1	57.4	74.9

Notes: The table reports moments from the distribution of the share of movers within universities. One observation is one university. These statistics are calculated on the total of students who enroll in a master degree in one of the 71 universities participating in the data collection (N=316,463).

Table 5: Summary Statistics - Sample selection

	Sample of analysis		Not in sample		
Variable	Mean	SD	Mean	SD	p-value
Age at enrollment	24.51	4.42	24.33	3.72	0.000
High-school type: liceo	0.77	0.421	0.798	0.402	0.000
GPA	27.53	1.58	27.66	1.61	0.000
Final grade degree	107.85	5.91	108.23	5.94	0.000
Actual lenght>legal lenght (*fuoricorso*)	0.413	0.597	0.435	0.605	0.000
Move to a different province (NUTS 3)	0.578	0.494	0.572	0.495	0.000
Move to a different region (NUTS 2)	0.295	0.456	0.31	0.462	0.000
N	127,150		189,313		

The table compares moments from the distributions of pre-Master characteristics and Master performance between units in the sample of analysis and units not in the sample. The unit of observation is an individual. The sample of analysis is defined as male and female students who answer to the survey one year after degree's completion, who work when the survey is conducted and who have non-missing wages. The last column reports a p-value on a test of comparison of means between the two groups.

Table 6: Summary Statistics - Pre-graduation variables

	Female (N=69,644)		Male (N=57,474)		
Variable	**Mean**	**SD**	**Mean**	**SD**	**p-value**
	Aministrative records - Student information				
Age at enrollment	24.49	4.55	24.54	4.25	0.07
High-school type: liceo	0.829	0.377	0.699	0.459	0.000
GPA in Master degree	27.73	1.488	27.29	1.66	0.000
Final grade in Master degree	108.48	5.53	107.09	6.26	0.000
Actual lenght>legal lenght (*fuoricorso*)	0.378	0.579	0.456	0.615	0.000
Move to a different province (NUTS 3) for univ.	0.592	0.491	0.596	0.496	0.000
Move to a different region (NUTS 2) for univ.	0.302	0.459	0.285	0.452	0.000
Female LFP in province of origin	50.73	10.97	50.77	11.01	0.51
Male LFP in province of origin	74.28	4.46	74.28	4.41	0.64
	Pre-graduation survey - Family background				
Matched to administrative records	0.917	0.276	0.896	0.305	0.000
Financial aid based on family income	0.238	0.426	0.208	0.406	0.000
Mother: university degree	0.18	0.384	0.207	0.405	0.000
Father: university degree	0.188	0.391	0.226	0.418	0.000
Mother: works	0.727	0.445	0.734	0.442	0.000
Mother: executive occupation	0.06	0.238	0.067	0.249	0.000
Father: executive occupation	0.181	0.385	0.215	0.411	0.000
Mother: teacher	0.131	0.337	0.148	0.355	0.000
Father: teacher	0.032	0.176	0.037	0.189	0.000
	Pre-graduation survey - Job-search aspirations				
Share attributing high value to: Salary	0.594	0.491	0.583	0.493	0.000
Share attributing high value to: Social utility	0.412	0.492	0.311	0.463	0.000
Share attributing high value to: Hours flexibility	0.305	0.46	0.289	0.453	0.000
Share attributing high value to: Leisure time	0.322	0.467	0.319	0.466	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 7: Summary Statistics - Post-graduation variables

	Female (N=69,644)		Male (N=57,474)		
Variable	**Mean**	**SD**	**Mean**	**SD**	**p-value**
	Post-graduation survey: LM outcomes				
Response rate	0.742	0.438	0.737	0.44	0.003
Have a job contract	0.539	0.498	0.618	0.486	0.000
Have children	0.043	0.203	0.029	0.168	0.000
Monthly earnings (€)	1073.98	496.37	1320.2	507.35	0.000
Full-time job	0.693	0.461	0.862	0.344	0.000
Weekly hours worked	33.09	13.05	38.67	10.75	0.000
Job location different from province of origin	0.441	0.496	0.516	0.50	0.000
Return to province of origin	0.255	0.436	0.196	0.397	0.000
Work abroad	0.049	0.217	0.052	0.223	0.000
High-wage occupation	0.573	0.495	0.769	0.421	0.000
High full-time occupation	0.503	0.50	0.734	0.442	0.000
Female-dominated occupation	0.701	0.458	0.412	0.492	0.000
High-wage industry	0.453	0.498	0.624	0.484	0.000
High full-time industry	0.525	0.50	0.743	0.437	0.000
Female-dominated industry	0.57	0.495	0.315	0.464	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 8: Selection of movers and students by province of origin

	Movers by provice of origin (Female)			All students by provice of origin (Female)		
	Low FLFP	High FLFP	Difference	Low FLFP	High FLFP	Difference
Characteristics of students						
Age at enrollment (years)	24.36	24.05	0.32	24.48	24.23	0.25
GPA (0/30)	27.66	27.91	-0.25	27.78	27.87	-0.09
Final grade prev. education (0-110)	100.94	101.94	-1	101.09	101.65	-0.56
Fraction with children	0.029	0.035	-0.006	0.034	0.041	-0.007
Fraction living with partner or married	0.15	0.18	-0.03	0.14	0.18	-0.04
Fraction with mother with tertiary educ.	0.18	0.19	-0.01	0.17	0.20	-0.03
Fraction with father with tertiary educ.	0.19	0.20	-0.01	0.18	0.21	-0.03
Fraction with mother in the labor force	0.59	0.84	-0.25	0.56	0.83	-0.28
Fraction with father in the labor force	0.99	0.99	0.00	0.99	0.99	0.00
Mobility and sorting						
Female LFP in province of studies (%)	49.65	59.98	-10.33	43.01	60.75	-17.73
Fraction in high-FLFP province of studies	0.25	0.55	-0.3	0.143	0.68	0.40
Mean FLFP in provs. of female peers	45.26	55.05	-9.79	40.80	55.52	-14.72
Mean FLFP in provs. of male peers	45.49	55.02	-9.54	40.93	55.46	-14.53
Size of degree	83.95	84.26	-0.31	85.85	79.70	6.15
Fraction in STEM education	0.22	0.19	0.03	0.23	0.20	0.03
Fraction in Economics and Business	0.14	0.17	-0.03	0.17	0.19	-0.02
Fraction in Humanities	0.21	0.24	-0.03	0.20	0.22	-0.02
Number of observations	28,252	27,802		48,896	44,103	

Notes:

Table 9: Selection of movers and students by province of origin

	Movers by provice of origin			Movers by provice of origin (within degree)		
	Low FLFP	High FLFP	Difference	Low FLFP	High FLFP	Difference
Characteristics of students						
Age at enrollment (years)	24.36	24.05	0.32	24.13	24.28	-0.15
GPA (0/30)	27.66	27.91	-0.25	27.67	27.9	-0.23**
Final grade prev. education (0-110)	100.94	101.94	-1	101.23	101.65	-0.42
Fraction living with partner or married	0.15	0.18	-0.03	0.15	0.18	-0.03***
Fraction with mother with tertiary educ.	0.18	0.19	-0.01	0.20	0.18	0.02
Fraction with father with tertiary educ.	0.19	0.20	-0.01	0.20	0.18	0.02
Fraction with mother in the labor force	0.59	0.84	-0.25	0.62	0.81	-0.19**
Fraction with father in the labor force	0.99	0.99	0.00	0.99	0.99	0.00
Mobility and sorting						
Female LFP in province of studies (%)	49.65	59.98	-10.33			
Fraction in high-FLFP province of studies	0.25	0.55	-0.3			
Mean FLFP in provs. of female peers	45.26	55.05	-9.79			
Mean FLFP in provs. of male peers	45.49	55.02	-9.54			
Size of degree	83.95	84.26	-0.31			
Fraction in STEM education	0.22	0.19	0.03			
Fraction in Economics and Business	0.14	0.17	-0.03			
Fraction in Humanities	0.21	0.24	-0.03			
Number of observations	28,252	27,802		28,252	27,802	

Notes:

Table 10: Epidemiological approach

	Log(monthly earnings)			Log(weekly hours)			Pr(fulltime)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High FLFP prov.	0.089***	0.055***	0.056***	0.084***	0.054***	0.055***	0.045***	0.017**	0.018**
	(0.0159)	(0.0094)	(0.0091)	(0.0.0149)	(0.0125)	(0.0124)	(0.0111)	(0.0077)	(0.0078)
Mother in labor force			X			X			X
Father's occupation			X			X			X
GPA			X			X			X
Degree FEs		X	X		X	X		X	X
Cohort		X	X		X	X		X	X
N	19,514	19,360	19,360	19,514	19,360	19,360	19,514	19,360	19,360

Notes:

Table 11: Gender differences in early-career labor market outcomes

c

	Log(monthly earnings)			Log(weekly hours)		Full-time job	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.111***	-0.112***	-0.062***	-0.08***	-0.081***	-0.05***	-0.051***
	(0.0041)	(0.004)	(0.003)	(0.0033)	(0.0033)	(0.0026)	(0.0025)
Academic performance		X	X		X		X
Weekly hours worked			X				
$\mathbb{1}$ {Full-time job}			X				
Degree FEs	X	X	X	X	X	X	X
Cohort FEs	X	X	X	X	X	X	X
R-squared	0.29	0.30	0.52	0.25	0.25	0.29	0.29
N	127,150	127,150	127,150	127,150	127,150	127,150	127,150

Notes: All specifications include degree (i.e. master times university) and cohort fixed effects. The sample includes male and female students who answer to the survey one year after degree's completion, who work when the survey is conducted and who have non-missing wages (127,150). Labor market outcomes are measured one year following graduation. Controls for academic performance include GPA and whether the student completed the program within the legal lenght of 2 years. Standard errors are clustered at the degree level.

Table 12: Balancing tests for cohort composition

	Student pre-determined characteristics:				
Dep. variable	**Age at enroll.**	**Female**	**BSc grade 25 pctile (%)**	**HS: liceo**	**Finan. aid**
(Mean dep. variable)	(24.4)	(0.58)	(0.27)	(0.79)	(0.24)
Average FLFP in peers' provs.:	-0.06	0.009	-0.006	-0.003	0.000
	(0.111)	(0.006)	(0.007)	(0.006)	(0.007)
Female LFP in own prov.	0.163***	-0.002	-0.013***	-0.032***	-0.089***
	(0.02)	(0.001)	(0.002)	(0.001)	(0.002)
Degree FEs	X	X	X	X	X
Cohort FEs	X	X	X	X	X
Dep. variable	**Mother works**	**Father exec.**	**Mother exec.**	**Mother teacher**	**Mother univ degree**
(Mean dep. variable)	(0.72)	(0.33)	(0.11)	(0.14)	(0.20)
Average FLFP in peers' provs.:	0.003	-0.001	-0.003	-0.003	-0.006
	(0.006)	(0.007)	(0.004)	(0.005)	(0.005)
Female LFP in own prov.	0.076***	0.029***	0.018***	-0.023***	0.007***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Degree FEs	X	X	X	X	X
Cohort FEs	X	X	X	X	X

Notes: Each column reports the coefficients from a regression of the corresponding dependent variable (e.g. a student's age at enrollment) on the mean female LFP in peers' province of origin and the female LFP in the own province of origin. Each regression includes degree and cohort FEs. Standard errors (in parentheses) are clustered at the degree level. Both regressors are standardised. Average values of the dependent variable are shown below the variables' names. * Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 13: Balancing tests for cohort composition

	Average characteristics of peers in the same degree					
Dep. variable	**Age at enroll.**	**Female (%)**	**Final grade BSc**	**HS: liceo (%)**	**Mother works (%)**	**Father exec. (%)**
(Mean dep. variable)	(24.4)	(57.8)	(100.4)	(78.7)	(71.9)	(19)
Female LFP in own prov.	-0.001	0.03	0.004	-0.016	0.012	0.021
	(0.003)	(0.019)	(0.004)	(0.017)	(0.019)	(0.017)
Degree FEs	X	X	X	X	X	X
Cohort FEs	X	X	X	X	X	X

Notes: Each column reports the coefficient from a regression of the corresponding dependent variable - average characteristics of peers from the same degree - on the female LFP in the province of origin of the student. The regressor has been standardised. For example, a one standard deviation increase in the female LFP in the province of the student is not related to the mean age of the student's peers (Column 1). Each regression includes degree and cohort FEs. Standard errors (in parentheses) are clustered at the degree level. Average values of the dependent variable are shown below the variables' names. * Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 14: Raw and residual variation in peers' characteristics - Sample of Analysis

	Mean	**SD**	**Min**	**Max**
A: *Average female LFP in female peers' provinces*				
Raw cohort variable	50.47	8.14	27.33	66.66
Residuals: net of major and cohort FEs	0.00	1.6	-21.51	16.32
B: *Average female LFP in male peers' provinces*				
Raw cohort variable	50.53	8.16	27.33	66.66
Residuals: net of course and cohort FEs	0.00	1.84	-22.11	16.11
C: *Ratio FLFP/MLFP (%) in female peers' provinces*				
Raw cohort variable	67.14	8.75	43.61	85.36
Residuals: net of course and cohort FEs	0.00	1.85	-15.47	13.21
D: *Ratio FLFP/MLFP (%) in male peers' provinces*				
Raw cohort variable	67.14	8.75	43.02	85.36
Residuals: net of course and cohort FEs	0.00	1.82	-26.36	24.19
E: *Share of female peers with above-median ratio*				
Raw cohort variable	52.20	32.58	0	100
Residuals:	0.00	8.25	-90.85	60.23

Notes: The table reports descriptive statistics for specific peers' characteristics of interest, before (raw) and after (residual) removing degree and cohort FEs. These are computed on the sample of analysis: male and female students who answer the survey one year later and who are employed at the date of the survey after one year (N=127,150).

Table 15: Selection

Dependent variable	P(Respond survey)			P(Employment ∣ Respond)		
Sample	All	Female	Male	All	Female	Male
(Average)	(0.74)	(0.742)	(0.737)	(0.572)	(0.539)	(0.618)
	(1)	(2)	(3)	(4)	(5)	(6)
FLFP in own prov. of origin	-0.0101***	-0.0110***	-0.0091***	0.0357***	0.0451***	0.023***
	(0.0012)	(0.0014)	(0.0018)	(0.002)	(0.0022)	(0.0025)
FLFP in prov. of female peers	0.0009	-0.0038	0.0069	0.0018	0.0021	0.0027
	(0.0044)	(0.0065)	(0.006)	(0.0059)	(0.0084)	(0.0076)
FLFP in prov. of male peers	-0.0043	-0.0047	-0.0041	-0.0076	-0.0099*	-0.0023
	(0.0038)	(0.0046)	(0.0064)	(0.0048)	(0.0057)	(0.0078)
Degree FEs	X	X	X	X	X	X
Cohort FEs	X	X	X	X	X	X
N	314,299	181,574	132,725	232,498	134,679	97,818

Notes: All regressions include degree and cohort FEs. The sample in (1) includes the universe of graduates (N=314,299) of both genders. The sample in (4) includes graduates who respond to the survey. Regressors are standardised. Being employed is defined as having a labor contract (internships, apprenticeships and training programs are excluded). Standard errors are clustered at the degree level. * Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 16: Effects of peers on earnings and labor supply - Female sample

	Log(earnings)			**Log(weekly hours)**	**P(Fulltime)**
	(1)	(2)	(3)	(4)	(5)
FLFP in own province of origin	0.0189***	0.0192***	0.0118***	0.0148***	0.0017
	(0.0033)	(0.0033)	(0.0028)	(0.0033)	(0.0025)
Mean FLFP in province of female peers	0.0362***	0.036***	0.0198*	0.0299***	0.0186**
	(0.0125)	(0.0126)	(0.0116)	(0.0122)	(0.0094)
Mean FLFP in province of male peers	-0.0007	-0.0007	-0.0006	-0.0056	-0.0019
	(0.01)	(0.01)	(0.0093)	(0.0093)	(0.0073)
Academic performance		X	X		
Weekly hours worked			X		
Degree FEs	X	X	X	X	X
Cohort FEs	X	X	X	X	X
R-squared	0.29	0.29	0.47	0.23	0.28
N	69,644	69,644	69,644	69,644	69,644

Notes: All regressions include degree and cohort FEs. The sample includes female graduates who answer the post-graduation survey and who are employed at the date of the survey (N=69,644). All regressors are standardised. Controls for academic performance include GPA and a categorical variable for regularity of studies (based on actual duration vs. legal duration). Standard errors are clustered at the degree level. * Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 17: Effects of peers on other outcomes - Female sample

	Occupation type:		Industry type:			
	High wage	High fulltime	High wage	High fulltime	Children	Change prov.
	(1)	(2)	(3)	(4)	(5)	(6)
FLFP in own province of origin	0.0063***	0.0057***	0.0057**	0.0044*	0.0125***	-0.1835***
	(0.0023)	(0.0021)	(0.0025)	(0.0024)	(0.0012)	(0.0046)
FLFP in prov. of female peers	0.0235**	0.0225**	0.0065	0.0127	-0.0049	0.0051
	(0.0092)	(0.009)	(0.0092)	(0.0092)	(0.0056)	(0.0099)
FLFP in prov. of male peers	-0.0063	-0.0069	-0.0048	-0.0083	-0.0037	0.0081
	(0.0066)	(0.0065)	(0.0069)	(0.0072)	(0.0051)	(0.0069)
Degree FEs	X	X	X	X	X	X
Cohort FEs	X	X	X	X	X	X
R-squared	0.38	0.45	0.34	0.37	0.15	0.17
N	69,644	69,644	69,644	69,644	69,644	69,644

Notes: All regressions include degree and cohort fixed effects. The sample includes female graduates who answer the post-graduation survey and who are employed at the date of the survey (N=69,644). All regressors are standardised. Controls for academic performance include GPA and a categorical variable for regularity of studies (based on actual duration vs. legal duration). Standard errors are clustered at the degree level. * Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 18: Effects of peers on LM outcomes - Male sample

				Occupation type:	
	Log(earn.)	Log(hours)	Fulltime	High wage	High fulltime
	(1)	(2)	(3)	(4)	(5)
FLFP in own province of origin	0.0072**	0.009***	0.0034*	-0.001	-0.0014
	(0.0028)	(0.0024)	(0.0018)	(0.0021)	(0.0021)
Mean FLFP in province of female peers	0.0135	-0.0009	-0.0011	0.0061	0.0079
	(0.0083)	(0.0076)	(0.0056)	(0.0070)	(0.0069)
Mean FLFP in province of male peers	0.0123	-0.0075	0.0036	-0.0018	-0.0027
	(0.011)	(0.0098)	(0.008)	(0.009)	(0.0089)
Degree FEs	X	X	X	X	X
Cohort FEs	X	X	X	X	X
R-squared	0.25	0.23	0.27	0.38	0.45
N	57,474	57,474	57,474	57,474	57,474

Notes: All regressions include degree and cohort FEs. The sample includes male graduates who answer the post-graduation survey and who are employed at the date of the survey (N=57,474). All regressors are standardised. Standard errors are clustered at the degree level. Two alternative proxies for culture are used: female LFP (above) and the ratio of female to male LFP (below).

Table 19: Robustness Analysis - Female sample

Dep. variable: Log(earnings)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FLFP in own prov. of origin	0.0176***	0.0172***		0.0174***		0.0167***	
	(0.0034)	(0.0035)		(0.0034)		(0.0034)	
FLFP in prov. of female peers	0.0382***	0.0377***		0.0377***		0.0365***	
	(0.012)	(0.0121)		(0.012)		(0.0121)	
FLFP in prov. of male peers	0.0033	0.002		0.0029		0.0032	
	(0.0095)	(0.0096)		(0.0095)		(0.0096)	
$\mathbb{1}$ {Mother works}		0.0067	0.0102*				
		(0.0055)	(0.0054)				
Share of female peers with work. mothers		0.0011	0.0025				
		(0.0042)	(0.0042)				
Share of male peers with work. mothers		0.004	0.0043				
		(0.0032)	(0.0032)				
$\mathbb{1}$ {Mother executive }				0.0207**	0.0225**		
				(0.0093)	(0.0093)		
Share of female peers with mothers exec.				0.0029	0.0033		
				(0.0028)	(0.0028)		
Share of male peers with mothers exec.				0.0043	0.0045		
				(0.003)	(0.003)		
$\mathbb{1}$ {Father executive}						0.0291***	0.0306***
						(0.0055)	(0.0055)
Share of female peers with fathers exec.						0.0006	0.0013
						(0.003)	(0.003)
Share of male peers with fathers exec.						-0.0013	-0.0012
						(0.0028)	(0.0028)

Notes: All specifications include degree and cohort FEs. The sample of analysis is restricted to female students with non-missing information on parental background (62,855). All regressors are standardised. Standard errors are clustered at the degree level.

Table 20: Effects of peers on job-search aspirations - Female sample

Dependent variable	Social utility	Leisure time	Hours flexibility
(mean)	(0.41)	(0.32)	(0.31)
	(1)	(2)	(3)
FLFP in own province of origin	-0.023***	-0.0166***	-0.0149***
	(0.0017)	(0.0017)	(0.0019)
FLFP in provinces of female peers	-0.0119*	-0.0117*	-0.0091
	(0.007)	(0.0071)	(0.0071)
FLFP in provinces of male peers	0.0005	0.0011	-0.0043
	(0.0049)	(0.0052)	(0.0051)
Degree FEs	X	X	X
Cohort FEs	X	X	X
R-squared	0.09	0.03	0.03

Dependent variable	Social utility	Leisure time	Hours flexibility
FLFP/MLFP in own province of origin	-0.022***	-0.016***	-0.0143***
	(0.0017)	(0.0017)	(0.0018)
FLFP/MLFP in provinces of female peers	-0.014**	-0.0117*	-0.0106
	(0.0067)	(0.0069)	(0.0069)
FLFP/MLFP in provinces of male peers	0.0013	0.0016	-0.0035
	(0.0048)	(0.005)	(0.0048)
Degree FEs	X	X	X
Cohort FEs	X	X	X
R-squared	0.09	0.03	0.03

Notes: All regressions include degree and cohort FEs. The sample includes female students who answer the pre-graduation survey and who have non-missing information on job-search aspirations (N=164,212). The dependent variable is an indicator of whether the student gives high value to corresponding job attributes. Answers come the question: "How much do you value X in the job you are searching?" (scale 0-5). Sample averages are shown in parentheses. Regressors are standardised. Standard errors are clustered at the degree level. * Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 21: Robustness checks - Alternative measure of culture

	Female sample			Male sample		
	log(earn.)	log(hours)	fulltime	log(earn.)	log(hours)	fulltime
	(1)	(2)	(3)	(4)	(5)	(6)
FLFP/MLFP in own prov. of origin	0.0178***	0.0142***	0.0014	0.0058***	0.0079***	0.0022
	(0.0033)	(0.0033)	(0.0025)	(0.0028)	(0.0024)	(0.0017)
FLFP/MLFP in prov. of female peers	0.0337***	0.0258**	0.0189**	0.0119	-0.0019	-0.0029
	(0.0121)	(0.0119)	(0.0091)	(0.008)	(0.0074)	(0.0054)
FLFP/MLFP in prov. of male peers	-0.0002	-0.0043	-0.0032	0.0118	-0.0032	0.0064
	(0.0098)	(0.0091)	(0.0072)	(0.0107)	(0.0095)	(0.0078)
Degree FEs	X	X	X	X	X	X
Cohort FEs	X	X	X	X	X	X
N	69,644	69,644	69,644	57,474	57,474	57,474

Notes: All regressions include degree and cohort fixed effects. The sample includes female graduates who answer the post-graduation survey and are employed at the date of the survey. All regressors are standardised. Standard errors are clustered at the degree level. * Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 22: Non-linearities if the effects of peers - Female sample

Dep. variable: Log(earnings)	Q1		Q2		Q3		Q4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of female peers from Q1 (FLFP) - int.	-0.0352**		-0.026*		-0.0081		-0.0067	
	(0.016)		(0.0144)		(0.0173)		(0.0159)	
Share of female peers from Q4 (FLFP) - int.		0.0069		0.0121		0.0211**		0.0082
		(0.0113)		(0.0102)		(0.0098)		(0.0095)
Share of female peers from Q1 (FLFP)		X		X		X		X
Share of female peers from Q4 (FLFP)	X		X		X		X	
Share of male peers from Q1 (FLFP)	X	X	X	X	X	X	X	X
Share of male peers from Q4 (FLFP)	X	X	X	X	X	X	X	X
Quartile FLFP in own prov.	X							
Degree FEs	X	X	X	X	X	X	X	X
Cohort FEs	X	X	X	X	X	X	X	X
N	69,644	69,644	69,644	69,644	69,644	69,644	69,644	69,644

Notes: Two regressions are estimated. Row 1: log(earnings) on the quartile of FLFP in the prov. of origin, the share of female peers in the bottom quartile of FLFP interacted with each quartile of FLFP in the province of origin, after controlling for the share of female peers in the top quartile of FLFP. Row 2: log(earnings) on the quartile of FLFP in the prov. of origin, the share of female peers in the top quartile of FLFP interacted with each quartile of FLFP in the province of origin, after controlling for the share of female peers in the bottom quartile of FLFP. Both regressions include degree and cohort FEs, as well as controls for male peers' quartiles. The sample includes female graduates who both answer the post-graduation survey and are employed at the date of the survey. All regressors are standardised. Standard errors are clustered at the degree level. * Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 23: Cross-effects of peers and familial role models - Female sample

	Log(earnings)			Log(weekly hours)		
	(1)	(2)	(3)	(4)	(5)	(6)
FLFP in own province of origin	0.0182***	0.0182***	0.0175***	0.0151***	0.0147***	0.0142***
	(0.0034)	(0.0034)	(0.0034)	(0.0035)	(0.0034)	(0.0034)
FLFP in prov. of female peers (a)	0.0484***	0.0409***	0.0382***	0.0338**	0.0286**	0.0243*
	(0.0131)	(0.0123)	(0.0124)	(0.0135)	(0.0127)	(0.0128)
$\mathbb{1}$ {Mother works} (b)	0.0066**			0.0002		
	(0.0054)			(0.0053)		
(a)*(b)	-0.0111**			-0.0085*		
	(0.0057)			(0.0051)		
$\mathbb{1}$ {Mother executive} (c)		0.0252**			0.0253***	
		(0.0099)			(0.0095)	
(a)*(c)		-0.0168			-0.021*	
		(0.0114)			(0.0113)	
$\mathbb{1}$ {Father executive} (d)			0.0299***			0.0195***
			(0.0058)			(0.0059)
(a)*(d)			-0.0026			-0.0012
			(0.0065)			(0.0067)
FLFP in prov. of male peers	X	X	X	X	X	X
Degree FEs	X	X	X	X	X	X
Cohort FEs	X	X	X	X	X	X
N	62,530	62,530	62,530	62,530	62,530	62,530

Notes: All regressions include degree and cohort fixed effects. The sample includes female graduates who both (1) answer the post-graduation survey and are employed at the date of the survey, and (2) who have non-missing information on parental background (N=62,530). All regressors are standardised. Standard errors are clustered at the degree level. * Significant at 10%; **Significant at 5%; ***Significant at 1%.

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