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

Federica Meluzzi †

Preliminary Draft - Please Do Not Circulate

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 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.

*I am grateful to Pierre Cahuc and Arne Uhlendorff for their invaluable guidance, and to Francis Kramarz, Camille Landais, Roland Rathelot and Pauline Rossi for their suggestions at different stages. I also thank Ghazala Azmat, Alberto Bisin, Yann Bramoullé, Pauline Carry, Patricia Cortes, Gordon Dahl, Matthias Doepke, Alexandra De Gendre, Antoine Ferey, Raquel Fernandez, Paola Giuliano, Claudia Goldin, Libertad Gonzalez, Xavier Jaravel, Andreas Kotsadam, Alan Manning, Arnaud Maurel, Guy Michaels, Barbara Petrongolo, Alessandro Riboni, Nina Roussille, Nicolas Salamanca, Michela Tincani and Yves Zenou, as well as conference and seminar participants at SOLE Annual Congress (2023), SaM Workshop (2023), AMSE, CREST and LSE, for valuable feedbacks. I acknowledge funding from Fondazione Luigi Einaudi, Chaire sécurisation des parcours professionnels and EUR DATA EFM.

†PhD Candidate, CREST (Institut Polytechnique de Paris). E-mail: federica.meluzzi@ensae.fr

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 the 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 labor market choices (Akerlof and Kranton 2000), leading to large gender differences in time allocation - such between home and market work - and earnings, among other outcomes[1]. As such, gender norms are regarded as obstacles to achieving gender parity in the labor market. According to previous research, the slowdown in gender convergence has coincided with a slowdown in cultural norms since the 1990s (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. 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 initial uncertainty on the long-run 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 by observing signals from societal role models, such as the working behavior of women from the previous generation[2]. In these settings, present shocks to female 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 can spur social learning. Individuals can 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 classmates. The focus is on Italy, a developped country that offers significant spatial variation in cultural 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 regions (EVS 1990-2008). Cross-regional differences also emerge in house-

[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.

holds' time allocation, with women spending from 3 to 6 times more hours in home work than their male partners (Time Use Survey, 2008). To proxy for these differences in cultural norms, I rely on granular spatial heterogeneity in past female labor force participation (LFP)[3]. Behind is the idea that women who were raised in provinces with low levels of female LFP hold different gender identity beliefs than women raised in high-FLFP areas.

The empirical strategy is to identify the role of peers' culture on women's labor market choices 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 of 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 program, 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 elicited gender norms, past values of female LFP exhibit substantial variation across provinces (NUTS 3 classification), ranging from 29% to 66%. Second, owing to features of the university system, students are highly mobile: 58% 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: in the median degree, 59% of students are *movers*. Third, the size of degrees is relatively small, with half counting less than 57 students. Finally, I rely on data covering the universe of college graduates from all fields and universities in Italy. Importantly, this database cover 1,572 Master programs across multiple enrollment cohorts (2012-2016).

Owing to the data structure, my identification strategy plausibly 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 across adjacent cohorts. The identification of peer 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

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

pre-enrollment student characteristics, including measures of pre-determined ability and family background.

I start by establishing that women's labor market outcomes, such as their earnings and hours worked, relate to past values of female LFP in their province of origin. Similar to the epidemiological approach of 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 (within the same university), women from high-FLFP areas work 5.4% more hours and earn correspondingly higher salaries per month than women from low-FLFP areas. This relationship is not mediated by future mobility decisions, and is unlikely driven by differential selection of movers from different areas. Importantly, the role of culture is both quantitatively larger and not confounded by maternal role models, based on rich information on mothers' occupation and education level.

My main finding is that the exposure to college classmates from high-FLFP provinces 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) average earnings or (ii) the share of full-time jobs, my findings indicate that peers also affect women's occupational choices, by leading to higher sorting towards high-earnings and long-hours occupations. Instead, peers do not affect sorting along other observed margins - such as a firm's industry and mobility decisions - nor they affect fertility in the short run.

Leveraging information on elicited job-search preferences, I shed light on a novel mechanism: peers exert an influence on women's preferences for job attributes, as stated during their job search. When socialised in cohorts with more 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. I interpret these findings as suggestive that changes in aspirations might drive the observed changes in labor market behavior, consistent with social learning and role models' explanations.

Secondly, I shed light on substantial heterogeneity in treatment effects based on the availability of alternative role models, which supports 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 scarcer maternal role models. Furthermore, building on the theoretical framework of 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. Results are indicative of strong asymmetries. While women coming from low-FLFP areas react strongly to peer influence, those raised in provinces with female LFP in the highest quartile are not found to assimilate the culture of peers from less egalitarian backgrounds, which supports the spillovers mechanism.

These effects are entirely driven by female classmates. Being exposed to male peers raised in high-FLFP provinces does not alter women's labor market choices along the observed dimensions. Moreover, when replicating the analysis on the male subsample, my findings indicate 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 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.

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 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.

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:

Spatial variation in cultural norms: Since the seminal contribution of Fernandez and Fogli 2009, most studies in the epidemiological approach exploited cross-countries differences in cultural norms. In this paper, I focus on Italy, a country that offers substantial geographical variation in gender norms. For example, the share 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 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 proxy for these differences in culture, I rely on variations in local female LFP. This is motivated by empirical evidence showing that gender attitudes and female LFP co-move Fernandez 2013. 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 5 (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.

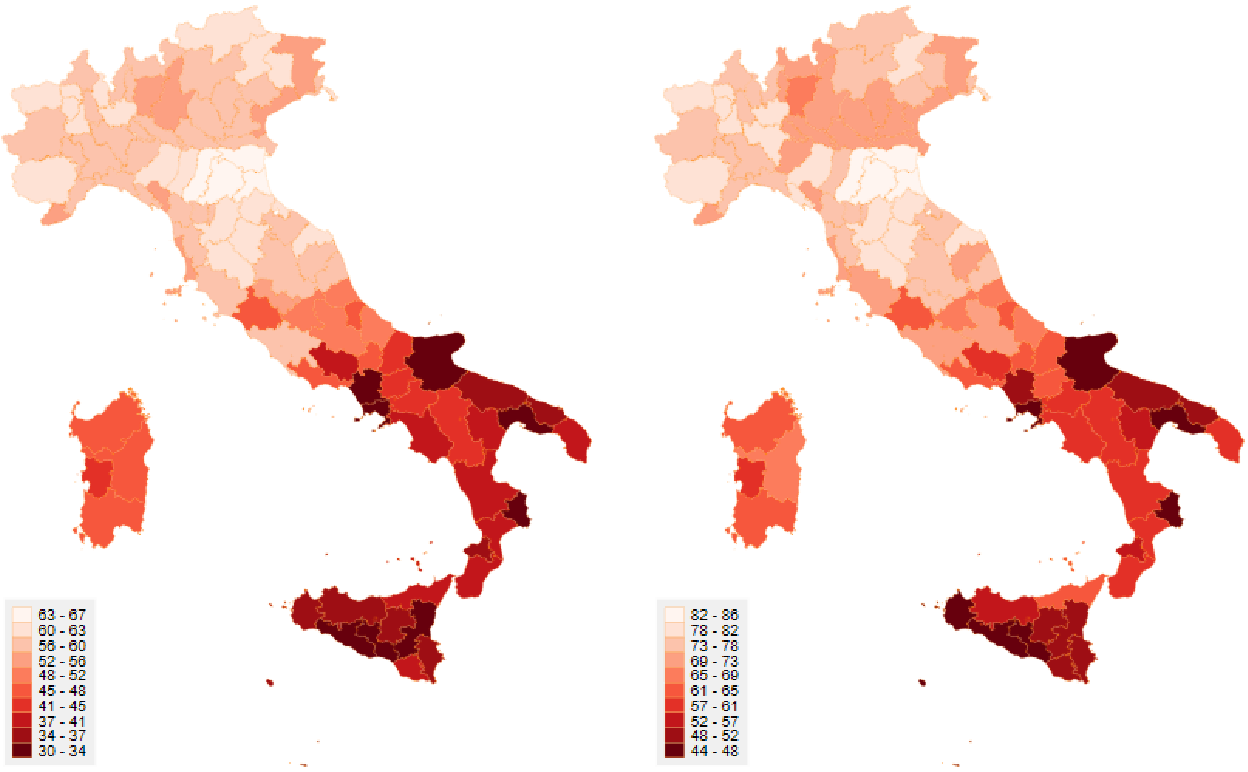
Throughout the paper, I will focus on provinces as a geographical unit. A *province* is an administrative division of intermediate level between a municipality and a region, that corresponds to the NUTS-3 classification[5]. Assignment of students to provinces is based on their province of residence at the enrollment 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

[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.

at variations 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 (%)

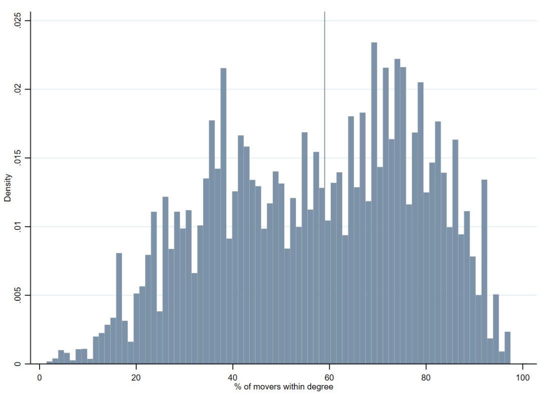
The maps represent female LFP (Panel a) and the ratio of female to male LFP (Panel b) across provinces in Italy. Each geographical partition is a province (NUTS 3 classification) and there are 107 provinces in total. Both measures are averages of the underlying variables over the years 2004-2007. They 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).

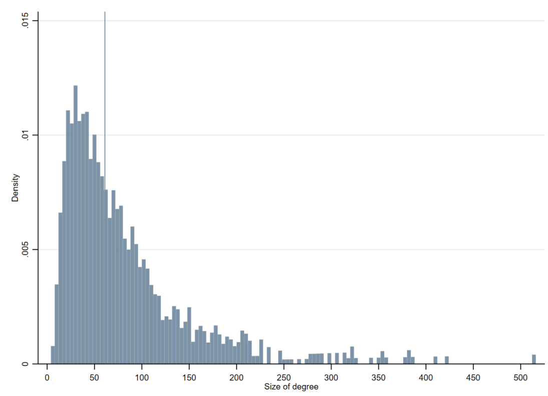
Students' mobility There are 96 universities in Italy, which are uniformly distributed across regions. Students apply to universities regardless of their place of residence. A large majority of universities are public and semi-public. Tuition fees are set autonomously by each academic institution. Students 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[6]. A distinctive feature of this setting is the high degree of mobility of students. In the years 2012-2016, around 58% (31%) of students move to another province (region) to pursue university. Note that I will refer to *movers* as students who move to another province hereafter. 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: the median degree accounts for 59% of movers, and this share ranges from 12% to 94% (Figure 2). 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 57 (32) students (Figure 2). Given the relatively small size of degrees, college classmates likely constitute a relevant peer group.

Figure 2: Share of movers and size of degrees

(a) Share of movers within a degree



(b) Size of degree



[6] Rattini 2022.

2.1 Insitutional background

2.2 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 will 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, and because the majority of undegraduate students pursue further education, I only focus on Master degrees. 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.

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 around 92% of the population of university students in Italy. 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 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.

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

4 Motivating facts

4.1 Gender gaps in earnings and labor supply

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). 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.

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

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 Culture and women's LM outcomes

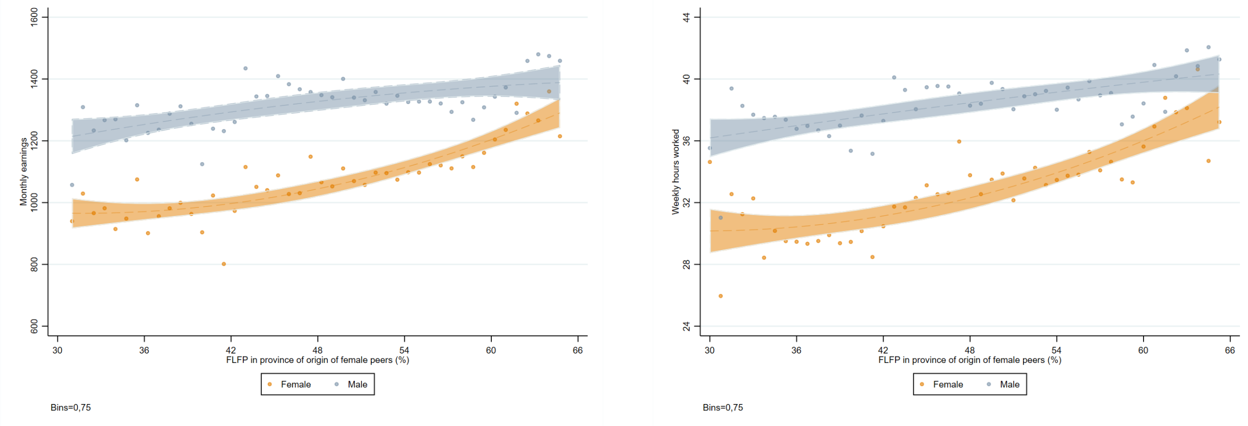
Table 10

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 orign. 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.

Figure 3: 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.

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 cohorts (2012-2016).

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

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.

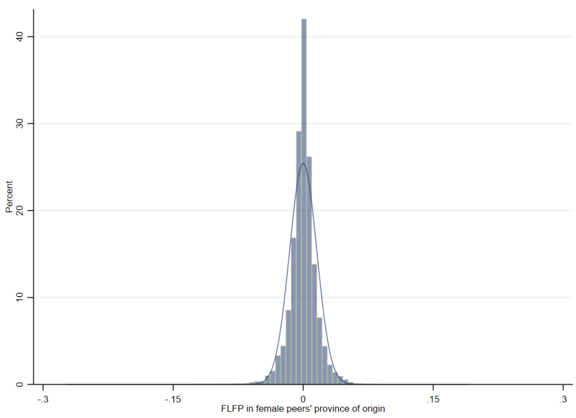
5.1 Support to the identification strategy

Threat to identification. One key concern in the identification of peer effects is that similarities in economic outcomes between individuals within a peer group arise because of *correlated effects*, in the Manski terminology (Manski 1993). In the presence of correlated effects, individuals within a peer group have similar individual characteristics, or face common institutional or economic shocks, that drive their outcomes, even when social influence is vacuous. In this setting, this translates into the possibility that cross-cohort changes in students' cultural composition within a degree are driven by unobserved factors - e.g. related to selection or common institutional shocks - that directly influence individual outcomes in the labor market. For this identification strategy to capture social influence, one needs, instead, that these cross-cohort fluctuations are as good as random.

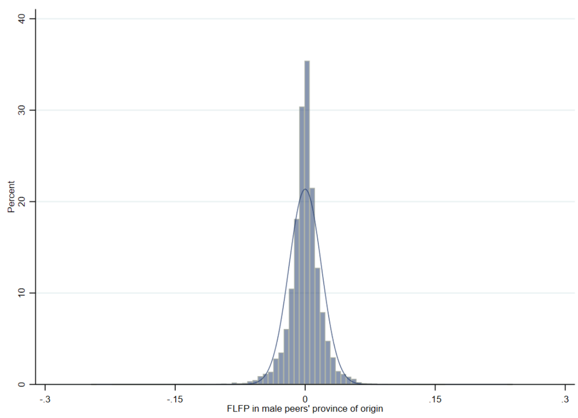
Balancing tests for cohort composition. One empirical test of this assumption is to verify that there is no selection, based on observables, into peer groups. Precisely, while students can select into fields of study and universities based on time-invariant characteristics - such as the average peers' composition - I need to rule out that student systematically sort into programs based on the specific composition of their cohort. To this aim, I perform an array of balancing tests and show that cross-cohort variations in peers' cultural composition, as measured by the average FLFP in peers' province of origin, are unrelated to a battery of pre-determined individual characteristics. The empirical model presented in (1) and (2) is estimated using a number of individual pre-determined covariates as outcome variables: age at enrollment, pre-determined ability (as measured by the probability to be in the highest and lowest quartiles based on final grades in Bachelor), type of high-school, eligibility to financial aid for low-SES students, and family composition, based on parents' occupations. The model is estimated separately on the subsamples of female and male students and results are shown in Tables 11 and 12, respectively. Results indicate that none of the estimated correlations appear to be significantly different from zero in the model. This analysis mitigates concerns regarding systematic differences due to sorting along observable students' characteristics. Based on Altonji, Elder, and Taber 2005, because of the richness and relevance of observables, we can reasonably believe that the degree of selection on observables can provide a good indicator of the degree of selection on unobservables.

As a further randomization check, I inspect whether shocks to peers' cultural composition can be regarded *as good as random*. Figure 4 plots the average FLFP in peers' provinces - separately for female peers (Panel a) and male peers (Panel b) - after removing degree and cohort FEs. Figure 6 in the Appendix does the same using the ratio of FLFP to MLFP as an alternative measure for culture. Cross-cohort changes in these measures follow closely a normal distribution, which adds credibility to the identifying assumption.

Figure 4: 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 peers' provinces of origin, by peers' gender, on degree and cohort FEs. It is plotted against the normal distribution for comparison.

Further inspections. Evidence provided in the balancing tests supports the hypothesis that year-to-year changes in students' geographical composition are not stemming from selection. However, this does not fully rule out the possibility that contemporaneous institutional changes, such as shocks to local labor markets, (that might, even coincidentally, correlate with changes in students' composition) might drive differences in outcomes across cohorts of students. I alleviate these concerns through a number of robustness exercises, by (1) enriching the model with region times year FEs and (2) by showing that the magnitude of peer influence does exhibit remarkable spatial heterogeneity.

Variation in peers' geographical composition. Implementing this empirical strategy requires that there is sufficient residual variation in peers' geographical composition after removing degree and cohort fixed effects. Table 13 contains moments from the distribution of peers' culture, as measured by the FLFP (or the ratio of FLFP/MLFP) in the province of origin. The total variation in female LFP in female (male) peers' provinces is 8.14 (8.16) percentage points, while the residual variation, once removing degree and cohort FEs, is 1.6 (1.84) pps. This means that around one fifth of the total variation in peers' culture is left unexplained: I rely on this variation to estimate peer effects.

6 Main Results

Earnings and Labor Supply. Estimates of the empirical model presented in (1) and (2) are shown separately on the subsamples of female and male students, in Table 15 and 16 respectively. The outcome variables are monthly earnings, weekly hours worked and hourly wages, all in logarithmic forms, and a full-time indicator. 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 in Table 15 indicate that the social environment in which women are socialized at university affects their early-career labor market choices. Specifically, being exposed to female classmates from high-FLFP provinces increases their labor supply along the intensive margin, both through higher take-up of full-time jobs and an increase 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 (as represented by $\Delta\overline{FLFP}^{FP}_{-i,dc}$ =8.14 pps.) leads to an increase of around 3% in both monthly earnings and weekly hours worked and raises the take-up of full-time jobs by 1.7 pps., a 2.5% increase relative to the mean. Hourly wages are not affected. Furthermore, there is no effect from male peers, a result that I will discuss later in the paper. Adjustments in women's labor supply are partly explained by changes in occupational sorting.

Sorting into occupations and industries. In Table 17, I estimate the empirical model on the probability of being employed in high-earnings or high-fulltime occupations and industries (Columns 1-4). To classify occupations (or industries) as high-earnings or high-fulltime, I proceed 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 in the relative distribution based on (i) or (ii).

According to these estimates, being exposed to female peers from high-FLFP provinces leads to higher sorting of women towards occupations with higher earnings and incidence of full-time jobs (Columns 1-2). The interpretation of this magnitude implies that a one standard deviation increase in the culture of female peers raises the likelihood that a woman chooses a high-earnings occupation by 2 pps., a 3.4% increase relative to the mean. Instead, peers do not affect sorting towards industry types (Columns 3-4). To quantify the importance of changes in occupational sorting in explaining the increase in women's abor supply, I re-estimate the empirical model on weekly hours worked while adding occupation and industry fixed effects. If compared to Column 2 of Table 15, the estimated δ_{FP} has decreased in magnitude, indicating that around one third of the variation in female labor supply comes from changes in occupations. However, most of the increase in female labor supply does not relate to changes in occupations nor industries.

Treatment effects on male students. The empirical analysis is performend separately on the male subsample and results are shown in Table 16 and 18. First, labor market outcomes of male students exhibit little or no relationship with the female LFP in their province of origin, consistent with the idea that FLFP in the province of origin is a proxy for a woman's identity beliefs. Moreover, their labor supply decisions, and their earnings, are not affected by changes in their peers' geographical compositions, regardless of their classmates' gender. Absence of an effect on male students provides support to the interpretation of cultural assimilation.

7 Robustness analysis

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 19. 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[10] or degrees that are in the first quartile in the share of movers from other provinces[11] (Table 21).

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 δ^{FP} and δ^{MP} are able to measure the effects of the social environment rather than spurious relationships. Even in a setting that allows

[10] 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)

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

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 8, 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 22, I replicate the empirical analysis by controlling for alternative peers' characteristics[12]. Estimates of δ^{FP} and δ^{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 23).

Other concerns. An alternative explanation to the observed effects, other than cultural assimilation, is that of network effects. Being exposed to peers from high-FLFP provinces might induce a positive information shock. For example, students might learn of other local labor markets with higher match quality or better conditions and might therefore follow their peers' mobility decisions. I will discuss this concern in the next section.

8 Mediation Analysis

[12]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)

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.

Results presented in Table 15 and Table 17 indicate that peer influence affects women's labor market coices, and that the effect comes entirely from other female classmates. Quasi-random exposure to male classmates from high-FLFP provinces does not affect women's initial labor market 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.

8.1 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.

9 Non-linearities and asymmetric peer effects

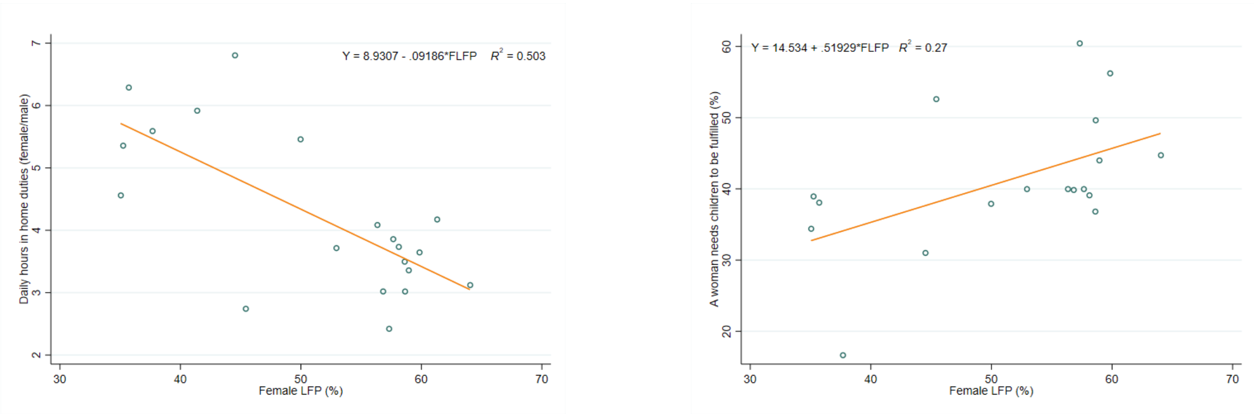
So far, I have relied on a linear-in-means model to uncover the average peer effect, hereby assuming that individuals are linearly affected by the mean culture of their peers. However, this hypothesis is too restrictive in many real-life situations. Rather, non-linearities in the effect of peers can 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.

10 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 3.6%, 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 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, 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%.

APPENDIX

Figure 5: 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 degrees

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 degrees. One observation is one degree. 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	0.42	0.80	0.40	0.000
Duration of studies>min. duration (*fuoricorso*)	0.36	0.48	0.37	0.48	0.000
GPA	27.53	1.58	27.66	1.61	0.000
Final grade	107.85	5.91	108.23	5.94	0.000
Move to a different province (NUTS 3)	0.58	0.49	0.57	0.49	0.000
Move to a different region (NUTS 2)	0.29	0.46	0.31	0.46	0.000
Female LFP in province of origin	50.75	10.99	48.96	11.21	0.000
Male LFP in province of origin	74.28	4.44	73.51	4.55	0.000
FLFP/MLFP (%) in province of origin	67.75	11.66	65.99	11.91	0.000
Female LFP in province of studies	54.12	9.98	52.66	10.67	0.000
Male LFP in province of studies	75.31	3.72	74.74	3.98	0.000
N	127,153		189,317		

The table compares moments from the distributions of students' characteristics between units in the sample of analysis and units not in the sample. The unit of observation is one student. The sample of analysis is defined as students who answer the survey one year after graduation, who are employed when the survey is conducted and who report 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=69,659)		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 7: 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 8: Selection of movers and students by province of origin

	Movers by province of origin			Movers by province of origin (within degree)		
	Low FLFP	High FLFP	Difference	Low FLFP	High FLFP	Difference
Characteristics of students						
Age at enrollment (years)	24.62	24.22	0.40***	24.13	24.28	-0.15
GPA during Master (0/30)	27.66	27.91	-0.25	27.67	27.89	-0.22***
Final grade prev. education (0-110)	100.94	101.94	-1	101.21	101.62	-0.41
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	-0.00	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	0.60	0.84	-0.23***	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 9: Culture and women's LM outcomes

	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 10: 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				
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 11: Balancing tests for cohort composition - Female students

	Student pre-determined characteristics:					
Dep. variable	**Enroll. age**	**Q4 pre-det GPA**	**Q1 pre-det GPA**	**High-school: liceo**	**Low-SES grant**	**Mother works**
(Mean dep. variable)	(24.4)	(0.20)	(0.27)	(0.79)	(0.23)	(0.72)
Female LFP in own prov.	0.182***	0.019***	-0.015***	-0.034***	-0.089***	0.077***
	(0.023)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Average FLFP in female peers' provs.:	-0.031	0.004	-0.009	0.002	-0.002	-0.004
	(0.092)	(0.007)	(0.007)	(0.005)	(0.007)	(0.006)
Average FLFP in male peers' provs.:	-0.111	0.004	0.000	-0.010***	0.007	-0.008
	(0.095)	(0.005)	(0.004)	(0.004)	(0.006)	(0.005)
Degree FEs	X	X	X	X	X	X
Cohort FEs	X	X	X	X	X	X
N	182,790	162,089	162,089	182,790	131,497	163,750
Dep. variable	**Mother: HS occ.**	**Mother: teacher**	**Mother: entrepr.**	**Father: HS occ.**	**Father: teacher**	**Father: entrepr.**
(Mean dep. variable)	(0.11)	(0.14)	(0.01)	(0.33)	(0.04)	(0.05)
Female LFP in own prov.	0.018***	-0.023***	0.001**	0.025***	-0.001***	0.000
	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)
Average FLFP in female peers' provs.:	-0.004	0.002	-0.002	-0.008	0.001	0.001
	(0.004)	(0.005)	(0.002)	(0.007)	(0.003)	(0.003)
Average FLFP in male peers' provs.:	-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	X	X	X	X	X	X
Cohort FEs	X	X	X	X	X	X
N	163,750	163,750	163,750	162,732	162,732	162,732

Notes: Each column reports the coefficients from a regression of the corresponding dependent variable on the mean FLFP in peers' province of origin and the FLFP in own province of origin. Each regression includes degree and cohort FEs. Standard errors (in parentheses) are clustered at the degree level. All regressors are standardised. The sample includes only female students (N=182,790). Sometimes, N is smaller due to missing observations.

Table 12: Balancing tests for cohort composition - Male students

	Student pre-determined characteristics:					
Dep. variable	**Enroll. age**	**Q4 pre-det GPA**	**Q1 pre-det GPA**	**High-school: liceo**	**Low-SES grant**	**Mother works**
(Mean dep. variable)	(24.4)	(0.20)	(0.27)	(0.79)	(0.23)	(0.72)
Female LFP in own prov.	0.129***	0.007***	-0.01***	-0.030***	-0.09***	0.075***
	(0.022)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
Average FLFP in female peers' provs.:	0.044	0.010	-0.001	0.006	0.006	-0.001
	(0.059)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
Average FLFP in male peers' provs.:	-0.072	0.001	0.006	-0.002	0.002	0.009
	(0.074)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)
Degree FEs	X	X	X	X	X	X
Cohort FEs	X	X	X	X	X	X
N	133,673	116,252	116,252	133,673	95,852	116,915
Dep. variable	**Mother: HS occ.**	**Mother: teacher**	**Mother: entrepr.**	**Father: HS occ.**	**Father: teacher**	**Father: entrepr.**
(Mean dep. variable)	(0.11)	(0.14)	(0.01)	(0.33)	(0.04)	(0.05)
Female LFP in own prov.	0.019***	-0.024***	0.001*	0.035***	-0.01***	0.002*
	(0.001)	(0.002)	(0.001)	(0.002)	(0.009)	(0.001)
Average 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)
Average 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	X	X	X	X	X	X
Cohort FEs	X	X	X	X	X	X
N	116,915	116,915	116,915	117,045	117,045	117,045

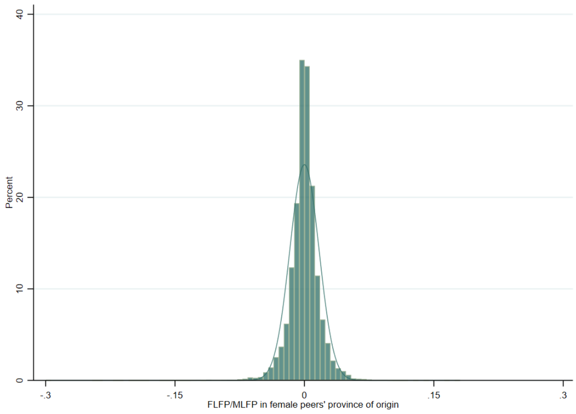
Notes: Each column reports the coefficients from a regression of the corresponding dependent variable on the mean FLFP in peers' province of origin and the FLFP in own province of origin. Each regression includes degree and cohort FEs. Standard errors (in parentheses) are clustered at the degree level. All regressors are standardised. The sample includes only male students (N=133,673). Sometimes, N is smaller due to missing observations.

Table 13: Raw and residual variation in peers' cultural composition

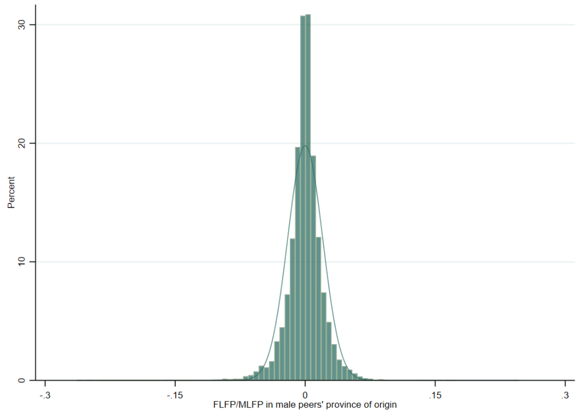
	Mean	SD	Min	Max
A: *Average FLFP in female peers' provinces*				
Raw cohort variable	50.47	8.14	27.33	66.66
Residuals: net of major and cohort FEs	0.00	1.6	-21.51	16.32
B: *Average FLFP in male peers' provinces*				
Raw cohort variable	50.53	8.16	27.33	66.66
Residuals: net of course and cohort FEs	0.00	1.84	-22.11	16.11
C: *Ratio FLFP/MLFP (%) in female peers' provinces*				
Raw cohort variable	67.48	8.51	43.02	85.36
Residuals: net of course and cohort FEs	0.00	1.73	-22.12	16.53
D: *Ratio FLFP/MLFP (%) in male peers' provinces*				
Raw cohort variable	67.53	8.54	43.02	85.36
Residuals: net of course and cohort FEs	0.00	1.99	-23.46	17.16

Notes: The table reports descriptive statistics for the main variables describing peers' cultural composition, 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).

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: 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 15: Treatment effects on earnings and labor supply - Female sample

	Log(earnings)	Log(weekly hours)	P(Fulltime)	Log(hourly wage)
	(1)	(2)	(3)	(4)
FLFP in own province of origin	0.0186***	0.0132***	0.0018	0.0054*
	(0.0033)	(0.0034)	(0.0025)	(0.0032)
Mean FLFP in province of female peers	0.0304**	0.0286**	0.0169*	0.0018
	(0.0125)	(0.012)	(0.0096)	(0.0126)
Mean FLFP in province of male peers	0.0005	0.002	-0.0017	-0.0015
	(0.0102)	(0.0093)	(0.0074)	(0.0098)
Degree FEs	X	X	X	X
Cohort FEs	X	X	X	X
R-squared	0.29	0.25	0.28	0.10
N	67,453	67,453	67,453	67,453

Notes: All regressions include degree and cohort FEs. The sample is restricted to female graduates (N=67,453). All regressors are standardised. Standard errors are clustered at the degree level. * Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 16: Treatment effects on earnings and labor supply - Male sample

	Log(earnings)	**Log(weekly hours)**	**P(Fulltime)**	**Log(hourly wage)**
	(1)	(2)	(3)	(4)
FLFP in own province of origin	0.007**	0.0084***	0.0034*	0.0029*
	(0.0028)	(0.0024)	(0.0018)	(0.0017)
Mean FLFP in province of female peers	0.0128	-0.001	-0.0004	0.0137*
	(0.0084)	(0.0077)	(0.0056)	(0.008)
Mean FLFP in province of male peers	0.0174	-0.0039	0.0033	0.0199*
	(0.0112)	(0.0102)	(0.0082)	(0.0103)
Degree FEs	X	X	X	X
Cohort FEs	X	X	X	X
R-squared	0.25	0.23	0.27	0.11
N	55,241	55,241	55,241	55,241

Notes: All regressions include degree and cohort FEs. The sample is restricted to female graduates (N=55,241). All regressors are standardised. Standard errors are clustered at the degree level. * Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 17: Treatment effects on other outcomes - Female sample

	Occupation:		Industry:		
	High-earnings	High-fulltime	High-earnings	High-fulltime	Log(weekly hours)
	(1)	(2)	(3)	(4)	(5)
FLFP in own province of origin	0.0066***	0.0057***	0.0061***	0.0037	0.0117***
	(0.0023)	(0.0022)	(0.0026)	(0.0025)	(0.0031)
Mean FLFP in province of female peers	0.0207**	0.0208**	0.0043	0.0053	0.0189*
	(0.0094)	(0.0092)	(0.0094)	(0.0091)	(0.011)
Mean FLFP in province of male peers	-0.0032	-0.0047	-0.0042	-0.0053	-0.003
	(0.0066)	(0.0064)	(0.007)	(0.0066)	(0.0089)
2-digit occupation FEs					X
2-digit Industry FEs					X
Degree FEs	X	X	X	X	X
Cohort FEs	X	X	X	X	X
Mean dependent variable	0.58	0.51	0.46	0.41	32.9
R-squared	0.38	0.45	0.34	0.39	0.09
N	67,453	67,453	67,453	67,453	67,453

Notes: The sample is restricted to female graduates (N=67,453). 2-digit occupations and industries are ranked based on their median earnings and share of full-time contracts. Indicators of high-earnings and high-fulltime are constructed based on position of ranking of occupation/industry relative to the median. All regressions include degree and cohort FEs. All regressors are standardised. Standard errors are clustered at the degree level. * Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 18: Treatment effects on other outcomes - Male sample

	Occupation:		Industry:		
	High-earnings	High-fulltime	High-earnings	High-fulltime	Log(weekly hours)
	(1)	(2)	(3)	(4)	(5)
FLFP in own province of origin	-0.001	-0.0014	-0.0008	-0.0009	0.006***
	(0.0021)	(0.0021)	(0.0027)	(0.0025)	(0.0023)
Mean FLFP in province of female peers	0.0045**	0.0055	-0.0069	-0.0091	-0.0013
	(0.0071)	(0.0069)	(0.0086)	(0.0083)	(0.0072)
Mean FLFP in province of male peers	0.0015	0.001	0.0188*	0.0199**	-0.007
	(0.0092)	(0.0091)	(0.0097)	(0.0088)	(0.009)
2-digit occupation FEs					X
2-digit Industry FEs					X
Degree FEs	X	X	X	X	X
Cohort FEs	X	X	X	X	X
Mean dependent variable	0.78	0.74	0.63	0.65	38.7
R-squared	0.38	0.45	0.31	0.40	0.35
N	55,241	55,241	55,241	55,241	55,241

Notes: The sample is restricted to female graduates (N=55,241). The sample size increases in Column 5 because it does not restrict to students with non-zero earnings. 2-digit occupations and industries are ranked based on their median salary and share of full-time contracts. Indicators of high-pay and high-fulltime are constructed based on position of one occupation/industry relative to the median. All regressions include degree and cohort FEs. All regressors are standardised. Standard errors are clustered at the degree level. * Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 19: Robustness checks 1 - Female sample

	Log(earnings)	Log(weekly hours)	P(Fulltime)	Log(hourly wage)
	(1)	(2)	(3)	(4)
Mean FLFP in province of female peers	0.0291**	0.025**	0.017*	0.0042
	(0.0126)	(0.0122)	(0.0096)	(0.0123)
Mean FLFP in province of male peers	-0.0009	-0.0003	-0.0025	-0.0005
	(0.0101)	(0.0095)	(0.0073)	(0.0095)
Region x Cohort FEs	X	X	X	X
Degree FEs	X	X	X	X
Cohort FEs	X	X	X	X
R-squared	0.29	0.25	0.28	0.10
N	67,453	67,453	67,453	67,453

Notes: All regressions include degree, cohort and region (of study) times cohort FEs. The sample is restricted to female graduates (N=67,453). All regressors are standardised. Standard errors are clustered at the degree level. * Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 20: Robustness checks 2 - Female sample

	Log(earnings)	**Log(earnings)**	**Log(earnings)**
	(1)	(2)	(3)
Mean FLFP in province of female peers	0.0393**	0.0308**	0.0281***
	(0.0177)	(0.0126)	(0.0138)
Mean FLFP in province of male peers	0.0085	0.003	0.0005
	(0.0139)	(0.0108)	(0.0110)
Exclude small degrees	X		
Exclude large degrees		X	
Exclude degrees with low share of movers			X
Degree FEs	X	X	X
Cohort FEs	X	X	X
R-squared	0.30	0.28	0.29
N	51,484	49,727	53,025

Notes: All regressions include degree and cohort FEs. The sample is restricted to female graduates (N=67,453). In Column 1, I exclude small degrees, i.e. degrees that are in the first quartile in the distribution of size (< 25 students). In Column 2, I exclude large degrees, i.e. degrees that are in the fourth quartile in the distribution of size (>124 students). In Column 3 I exclude degrees with low inflows of movers from other regions, i.e. those in the first quartile (<30%). All regressors are standardised. Standard errors are clustered at the degree level. * Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 21: Mediation analysis: performance - Female sample

	Log(Earnings)	**Log(hours)**	**P(fulltime)**	**GPA**
	(1)	(2)	(3)	(4)
FLFP in province of origin	0.0184***	0.0131***	0.0017	0.0527
	(0.0033)	(0.0034)	(0.0025)	(0.0078)
Avg. FLFP in female peers' provinces	0.0303**	0.0285**	0.0168*	0.0526
	(0.0125)	(0.012)	(0.0096)	(0.0307)
Avg. FLFP in male peers' provinces	0.0003	0.0019	-0.0019	0.0409
	(0.0102)	(0.0093)	(0.0074)	(0.0247)
GPA	X	X	X	
Degree Fes	X	X	X	X
Cohort Fes	X	X	X	X
R-squared	0.29	0.25	0.28	0.24
N	67,453	67,453	67,453	176,698

Table 22: Robustness Analysis - Female sample

	Log(Earnings)				Log(Weekly hours)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Avg. FLFP in female peers' provinces	0.0333***	0.0331***	0.0331***	0.0302**	0.0232*	0.0234*	0.0234*	0.0261**
	(0.0123)	(0.0122)	(0.0122)	(0.0123)	(0.0126)	(0.0125)	(0.0125)	(0.0126)
Avg. FLFP in male peers' provinces	0.0027	0.0037	0.0037	0.0041	-0.0005	0.0003	0.0003	-0.0026
	(0.0100)	(0.0098)	(0.0098)	(0.0098)	(0.0097)	(0.0096)	(0.0096)	(0.0094)
Mother works	X				X			
Share of peers with working mothers	X				X			
Mother in HS job		X				X		
Share of peers with mothers in HS job		X				X		
Father in HS job			X				X	
Share of peers with fathers in HS job			X				X	
Quartile of pre-det ability				X				X
Share of peers in quarts. of ability				X				X
FLFP in own provice of origin	X	X	X	X	X	X	X	X
Degree Fes	X	X	X	X	X	X	X	X
Cohort Fes	X	X	X	X	X	X	X	X
R-squared	0.29	0.29	0.29	0.29	0.25	0.25	0.25	0.25
N	60,896	60,896	60,896	60,165	60,896	60,896	60,896	60,165

Notes: All specifications include degree and cohort FEs. The sample of analysis is restricted to female students with non-missing information on parental background (60,896). Note that information on parental background is missing for 10% of the sample. Pre-determined ability is measured with a student's final grade in the Bachelor. Quartiles of performance are computed from the conditional distribution of grades within a university, to account for possible differences in grading systems. In all specifications, peers are separated by gender. All regressors are standardised. Standard errors are clustered at the degree level.

Table 23: Robustness checks 3 - FLFP/MFP as a proxy for 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	67,453	67,453	67,453	67,453	67,453	67,453

Notes: All regressions include degree and cohort FEs. The sample is restricted to female graduates (N=67,453). All regressors are standardised. Standard errors are clustered at the degree level. * Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 24: 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 25: 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 26: 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%.

References

[1] G. Akerlof and R. Kranton. "Economics and Identity". In: *Quarterly Journal of Economics* 115(3) (2000), pp. 715–753.

[2] A. Alesina, P. Giuliano, and N. Nunn. "ON THE ORIGINS OF GENDER ROLES: WOMEN AND THE PLOUGH". In: *The Quarterly Journal of Economics* 128(2) (2013), pp. 469–530.

[3] J.G. Altonji, T.E. Elder, and C.R. Taber. "Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools". In: *Journal of Political Economy* 113 (2005), pp. 151–184.

[4] G. Azmat and R. Ferrer. "Gender Gaps in Performance: Evidence from Young Lawyers". In: *Journal of Political Economy* 125(5) (2017), pp. 1306–1355.

[5] M. Bertrand, P. Cortes, C. Olivetti, and J. Pan. "Social Norms, Labor Market Opportunities, and the Marriage Gap Between Skilled and Unskilled Women". In: *Review of Economic Studies* 88(4) (2021), pp. 1936–1978.

[6] M. Bertrand, C. Goldin, and L. F. Katz. "Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors". In: *American Economic Journal: Applied Economics* 2(3) (2010), pp. 228–255.

[7] A. Bisin and T. Verdier. "BEYOND THE MELTING POT: CULTURAL TRANSMISSION, MARRIAGE, AND THE EVOLUTION OF ETHNIC AND RELIGIOUS TRAITS". In: *Quarterly Journal of Economics* CXV(3) (2000), pp. 955–988.

[8] F. D. Blau and L. M. Kahn. "The Gender Wage Gap: Extent, Trends, and Explanations". In: *Journal of Economic Literature* 55(3) (2017), pp. 789–865.

[9] B. Boelman, A. Raute, and U. Schönberg. "Wind of Change? Cultural Determinants of Maternal Labor Supply". In: *CESifo Working Paper No. 9094* (2021).

[10] V. Boucher, M. Rendall, P. Ushchev, and Y. Zenou. "Toward a General Theory of Peer Effects". In: *CEPR Discussion Paper No. DP17315* (2022).

[11] A.W. Cappelen, B. Tungodden, A. Voena, and D. Yanagizawa-Drott. "How Are Gender Norms Perceived?" In: *WORKING PAPER 31049* (2023).

[12] S. E. Carrell, M. Hoekstra, and E. Kuka. "The long-run effects of disruptive peers". In: *American Economic Review* 108(11) (2018), pp. 3377–3415.

[13] A. Casarico and S. Lattanzio. "Behind the Child Penalty: What Contributes to the Labour Market Costs of Motherhood". In: *Conditionally accepted at Journal of Population Economics* (2022).

[14] P. Cortes and J. Pan. "When Time Binds: Substitutes to Household Production, Returns to Working Long Hours and the Gender Wage Gap among the Highly Skilled". In: *Journal of Labor Economics* 37(2) (2019), pp. 351–398.

[15] P. Cortes, L. Pilossoph, E. Reuben, and B. Zafar. "Gender Differences in Job Search and the Earnings Gap: Evidence from the Field and the Lab". In: *Forthcoming at Quarterly Journal of Economics* (2022).

[16] P. Cortés, G. Koşar, J. Pan, and Z Basit. "Should Mothers Work? How Perceptions of the Social Norm Affect Individual Attitudes Toward Work in the U.S." In: *WORKING PAPER 30606* (2022).

[17] P. Cortés, G. Koşar, J. Pan, and B. Zafar. "Should Mothers Work? How Perceptions of the Social Norm Affect Individual Attitudes Toward Work in the U.S". In: *NBER Working Paper No. w30606* (2022).

[18] S. Currarini, M. O. Jackson, and P. Pin. "An economic model of friendship: Homophily, minorities, and segregation". In: *Econometrica* 77(4) (2009), pp. 1003–1045.

[19] EVS. "European Values Study Longitudinal Data File 1981-2008". In: (1990-2008). GESIS Data Archive, Cologne.

[20] R. Fernandez. "Women, Work, and Culture". In: *Journal of the European Economic Association* 5(2-3) (2007), pp. 305–332.

[21] R. Fernandez. "Cultural Change as Learning: The Evolution of Female Labor Force Participation over a Century". In: *American Economic Review* 103 (1) (2013), pp. 472–50.

[22] R. Fernandez and A. Fogli. "Fertility: The Role of Culture and Family Experience". In: *Journal of the European Economic Association* 4(2-3) (2006), pp. 552–561.

[23] R. Fernandez and A. Fogli. “Culture: An Empirical Investigation of Beliefs, Work, and Fertility”. In: *American Economic Journal: Macroeconomics* 1(1) (2009), pp. 146–177.

[24] A. Filippin and A. Ichino. “Gender Wage Gap in Expectations and Realizations”. In: *Labour Economics* 12(1) (2005), pp. 125–145.

[25] L. Flabbi and A. Moro. “The effect of job flexibility on female labor market outcomes: Estimates from a search and bargaining model”. In: *Journal of Econometrics* 168(1) (2012), pp. 81–95.

[26] A. Fogli and L. Veldkamp. “NATURE OR NURTURE? LEARNING AND THE GEOGRAPHY OF FEMALE LABOR FORCE PARTICIPATION”. In: *Econometrica* 79 (4) (2011), pp. 1103–1138.

[27] C. M. Hoxby. “The Effects of Class Size on Student Achievement: New Evidence from Population Variation”. In: *The Quarterly Journal of Economics* 115(4) (2000), pp. 1239–85.

[28] A. Ichino, M. Olsson, B. Petrongolo, and P. Skogman-Thoursie. “Economic incentives, childcare and gender identity norms”. In: *Work-in-progress* (2022).

[29] ISTAT. “STEREOTYPES ABOUT GENDER ROLES AND THE SOCIAL IMAGE OF SEXUAL VIOLENCE”. In: (2019).

[30] H. Kleven. “The Geography of Child Penalties and Gender Norms: Evidence from the United States”. In: *NBER Working Paper 30176* (2022).

[31] H. Kleven, C. Landais, and J. E. Søgaard. “Children and Gender Inequality: Evidence from Denmark”. In: *American Economic Journal: Applied Economics* 11 (4) (2019), pp. 181–209.

[32] I. Kuziemko, J. Pan, J. Shen, and E. Washington. “The Mommy Effect: Do Women Anticipate the Employment Effects of Motherhood?” In: *NBER Working Paper 24740* (2018).

[33] C.F. Manski. “Identification of Endogenous Social Effects: The Reflection Problem”. In: *The Review of Economic Studies* 60(3) (1993), pp. 531–542.

[34] E. C. A. Mertens, M. Deković, M. Van Londen, and E. Reitz. “The Role of Classmates’ Modeling and Reinforcement in Adolescents’ Perceived Classroom Peer Context”. In: *Journal of Youth and Adolescence* 50 (2021), pp. 260–270.

[35] M. B. Mertz, M. Ronchi, and V. Salvestrini. “Early exposure to entrepreneurship and the creation of female entrepreneurs”. In: *WP* (2022).

[36] C. Olivetti, E. Patacchini, and Y. Zenou. “Mothers, Peers and Gender-Role Identity”. In: *Journal of the European Economic Association* 18(1) (2020), pp. 266–301.

[37] E. Patacchini and Y. Zenou. “NEIGHBORHOOD EFFECTS AND PARENTAL INVOLVEMENT IN THE INTERGENERATIONAL TRANSMISSION OF EDUCATION”. In: *Journal of Regional Science* 51(5) (2011), pp. 987–1013.

[38] E. Patacchini and Y. Zenou. “Social networks and parental behavior in the intergenerational transmission of religion”. In: *Quantitative Economics* 7 (2016), pp. 969–995.

[39] V. Rattini. “The Effects of Financial Aid on Graduation and Labor Market Outcomes: New evidence from Matched Education-Labor Data”. In: *CESifo Working Paper No. 10010* (2022).

[40] B. Zafar and M. Wiswall. “Preference for the Workplace, Investment in Human Capital, and Gender”. In: *Quarterly Journal of Economics* 133(1) (2018), pp. 457–507.