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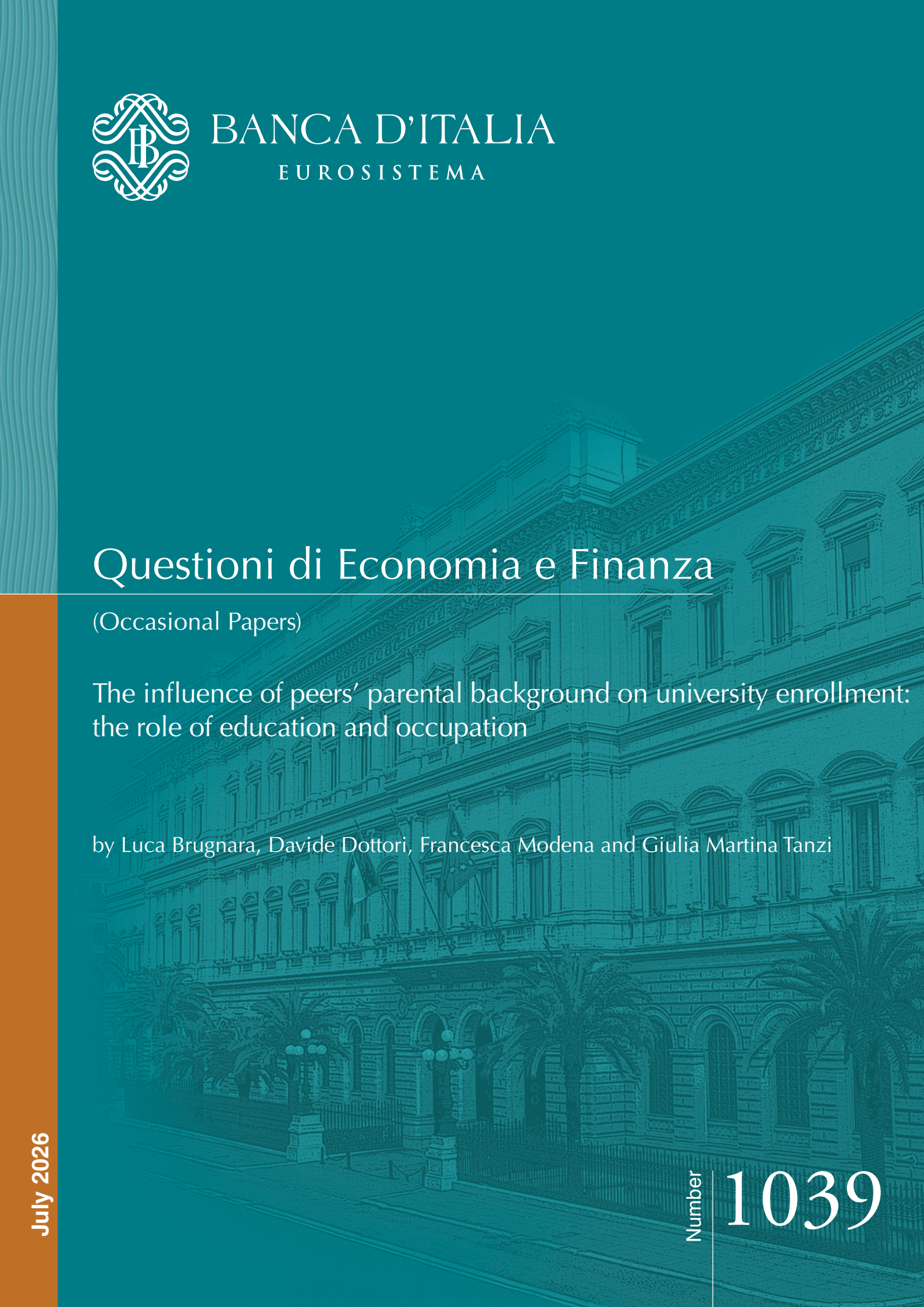

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THE INFLUENCE OF PEERS' PARENTAL BACKGROUND ON UNIVERSITY ENROLLMENT: THE ROLE OF EDUCATION AND OCCUPATION

by Luca Brugnara*, Davide Dottori**, Francesca Modena***
and Giulia Martina Tanzi****

Abstract

This paper investigates the influence of peers' parents in shaping high school students' decisions to enroll in university, highlighting the joint role of their education level and occupation. Using a rich longitudinal dataset on Italian students, we track individuals from high school to university enrollment and exploit within-school and cross-cohort variation to identify peer effects. Our results show that peers' parental education positively impacts university enrollment, and more strongly so when paired with the type of occupation.
These findings hold across students' and parents' gender and are more pronounced in non-academic schools and among students whose parents do not hold a university degree, suggesting that the peer effect is particularly relevant in contexts where the propensity to attend university is lower. The paper also finds that the peer effect is non-linear and strongest at intermediate levels of exposure, suggesting that a certain degree of diversity in the educational background of peers' parents may maximize the overall effect.

JEL Classification: I21, I23, I26, J24.

Keywords: university students' outcomes, peer effect, family background.

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1 Introduction [1]

Educational attainment has steadily increased over recent decades across all OECD countries but there remain significant disparities in the share of individuals attaining tertiary education (OECD (2025)). Interest in the determinants of students' educational choices has spurred considerable research over the past couple of decades. The interest today is more alive than ever, given the need to further increase the education level of the population in many countries and reduce the gender gap in specific fields of study.

Parental education, occupational status, and family income were found to be associated with educational achievement of the offsprings (Leppel et al., 2001; Björklund and Salvanes, 2011). As individuals enter adolescence, the family of origin ceases to be the only determinant of their choices, and the social context becomes a key source of influence: for instance, the peers have also been identified as an indisputable source of social pressure and imitation. Moreover, in the context of networks where individuals are directly or indirectly connected, the mothers and the fathers of the student's peers can be seen as another reference group, since they constitute a set of adults with whom the students may interact, about whom they have information from their peers, thereby influencing them.

The goal of this paper is to explore in detail the effect of the high-school peers' parental education and occupation on the decision of the student to enroll at university. Compared to the vast literature on parental influence, the role of the peers' parents is still relatively understudied. Only recently research has begun to explore how the education background of peers' parents can influence the students' educational and professional trajectories (Bifulco et al., 2011, 2014; Chung, 2020). In line with this stream of literature, we assess the effect on students' education choices of the peer parents' education level for the first time in the Italian context (to the best of our knowledge). We also consider that education per se is not enough but it more properly matters when jointly considered with occupation: the impact of the parents' high level of education in encouraging enrollment could be amplified by having obtained highly skilled occupations; conversely, the effect might be hampered if the parent is not employed or has a job in which the high level of human capital acquired is not required. In fact, observing overeducated parents may discourage boys and girls in undertaking tertiary education.

Peers' parental education and occupational status can influence the likelihood of enrolling at university in direct and indirect ways. Direct influences operate through situations and oc-

[1]We would like to thank Marco Tonello for valuable and helpful suggestions. We also thank for useful comments Raffaello Bronzini, Francesca Leombroni, Vincenzo Mariani, Roberto Torrini, Antonio Veronico, two anonymous reviewers and all other participants in the work-in-progress presentations held at Banca d'Italia. All remaining errors are authors' only responsibility.

casions of acquaintances with peers' parents, through which the student may directly observe the peer's family norms and aspirations, the attitude toward schooling and the value attached to higher education. Moreover, the students can receive further or more accurate and timely information about educational opportunities, financial aid or admission requirement than those they could obtain at their home. Indirect influence is by no means less important as often the same norms and information are conveyed by peers and circulate informally within the cohort in everyday life (Bisin and Verdier, 2001). Futhermore, peers' decisions – rooted in parental influence – indirectly reinforce college enrollment behavior since, when students hold incomplete beliefs about the returns to higher education, they often use the actions of their peers as a form of social learning. Both direct and indirect influences point out that even students with similar grades or abilities can be differentially exposed to college-relevant knowledge depending on the background of their peers' families (Granovetter, 2018).

There are two additional reasons why it is important to consider the effect of peers' parents on students, rather than focusing solely on the effect of the peers themselves. First, from a methodological point of view, college-going decisions among same-age peers are made simultaneously and are therefore vulnerable to issues of reverse causality, since students may influence each other in real time. By contrast, parents' educational attainment and occupational status are predetermined and exogenous to these contemporaneous decisions, making peer-parent characteristics a reliable indicator of the underlying social environment shaping students' college trajectories. Second, our empirical framework identifies the impact of parents' education and occupation while controlling for a rich set of peers' observable characteristics. As a result, any significant effect detected for peer parents' characteristics is identified over and above these compositional factors. For instance, we control for peers' average ability: if the share of peers with highly-educated parents mattered only for average ability, we should observe no significant coefficient on our variable of interest. A significant estimate therefore indicates that the parental peer effects go beyond that and ignoring them would lead to a lower understanding of the determinants of university enrollment.

Our analysis is based on a unique and very large dataset. Thanks to a student identifier, we can effectively combine two data sources: (i) data on secondary school students in Italy, providing information on the student's abilities and his/her family background, from which we can construct the peer-level variable, as well as the characteristics of schools and classes; (ii) administrative data covering all Italian students enrolled in university over an extended period of time.

To overcome the identification challenges, we exploit idiosyncratic variation in the education level and in the employment conditions of peers' parents across different cohorts of high school

students within a school. This approach, started with Hoxby (2000) been widely used to study peer effects in education and labor market outcomes (among others: Hanushek et al., 2003; Lavy et al., 2012; Anelli and Peri, 2019; Modena et al., 2022; Mouganie and Wang, 2020; Porreca et al., 2024). It allows to jointly control for school fixed effects (which account for endogenous sorting into school) and for time trends. Thanks to the richness of our dataset, we can also control for confounding factors related to student's own ability and family background, as well as for compositional variation at the class level within school. In this way, we are able to isolate the effect of differences in peers' parents for students that are as much as possible similar under a lot of dimensions (e.g.: same school, class characteristics, own ability, family background).

Our results show that, ceteris paribus, students exposed to a higher proportion of peers with highly-educated parents are more likely to enroll in university. More specifically, a one standard deviation increase in the share of such peers raises the probability of enrollment by 1 percentage points, corresponding to approximately 2% of the overall average enrollment rate. A comparison with the influence of parental education helps contextualise the size of the peer effect. When evaluated at the median size of the peer group, the results suggest that raising the share of peers with a university-educated parent by 10% leads to an increase in the likelihood of enrolling in higher education that amounts to roughly 18% of the effect associated with having a university-educated father.

Moreover, our findings reveal that not only does parental education matter, but so does the actual position in the labor market: when high educational attainment is coupled with unfavorable employment outcomes – such as no employment or holding a job for which a graduate is overqualified – the positive peer effect vanishes. Conversely, the peer effect becomes stronger when exposure is defined more narrowly, requiring both high parental education and a better alignment with the occupational outcome. Our analysis also verifies that it is really the high level of education that drives the peer effect, as exposure to peers whose parents hold at most a high-school diploma only exert a smaller impact, while exposure to peers' less educated parents has a negative effect.

Given the relevance of gender in the analysis of peer effects – particularly through channels such as role modeling – we broaden our investigation along this dimension, accounting for potential gender-specific differences related to both the students and their peers' parents. We find that the positive impact of peers' highly educated parents is confirmed for both male and female students and regards fathers and mothers. In addition, the estimates suggest the possible presence of a role model mechanism whereby a student is slightly more influenced by the peers' parents of the same gender. We also find that the impact of peers' parental education is higher for students of non-academic schools and of non-graduate parents, thus suggesting that in contexts with a

lower average propensity to pursue university education, the observation of peers' might play a more relevant role. Furthermore, by allowing for non-linearities in the econometric model, we find that the positive effect of peers' parental education emerges only when the share is not too low, and that it exhibits decreasing returns at the highest levels of the share.

Our study contributes to the literature in several ways. First, it relates to the strand of research examining the role of parental education in shaping students' educational choices. This literature, while established, remains relatively limited in scope and, to the best of our knowledge, does not include any evidence for Italy. Existing contributions show that exposure to peers with highly educated parents positively influences a range of students' outcomes, from college enrollment (Bifulco et al. (2011) and Bifulco et al. (2014)) to educational performance (Haraldsvik and Bonesrønning (2014) and McEwan (2003)), socio-emotional skills (Fruehwirth and Gagete-Miranda (2019)), test scores (Ammermueller and Pischke (2009)), and gender beliefs (Kim et al. (2021) and Eble and Hu (2019)). More recently, Cattan et al. (2025) show that exposure to high-school peers with elite-educated parents increases students' chances of enrolling in elite university programs (and later improves earnings).

Our study further contributes the literature analyzing the peers' parental effect on college attainment with respect to the joint combination of parental education and occupation, two dimensions that previous studies have addressed separately. This also connects our work to a more recent and smaller literature exploring the role of peers' parental occupational status on labour market outcomes. Olivetti et al. (2020) analyze whether a woman's labour supply as a young adult is shaped by the work behaviour of her adolescent peers' mothers.[2] Black et al. (2013) find that average earnings of peers' fathers matter for boys' educational choices and labour market outcomes.[3] Also the type of occupation chosen can be influenced by peers' parents: Mertz et al. (2024) investigates the effects of early exposure to entrepreneurs on the choice to become an entrepreneur; Montonen and Solomon (2024) explore the effect of the share of peers' parents with a white-collar job on long term students' occupational choices.

In this respect, our study can also be related to the strand of literature that uses the unemployment status of specific population groups (parents included) as a proxy for local economic conditions and examines how business-cycle fluctuations shape various educational choices and outcomes (Adamopoulou and Tanzi, 2017; Porreca et al., 2024). Differently from this line of research, we do not focus on economic downturns but rather on the alignment between parental education and occupations. We rely on parents' occupational categories to capture

[2]In a similar way Kleven et al. (2024) studies the effects on child penalties.

[3]Black et al. (2013) show that boys seem to benefit from being exposed to peers from very high-earning families but they are not hurt much from being exposed to peers from the opposite end of the distribution.

the favourable or unfavourable outcome of their educational trajectories, separating cases in which the acquisition of a high level of human capital is not aligned with the occupational position (irrespective of whether this is due to unemployment, house-keeping, inactivity or a blue-collar job).

In this setting, we introduce an innovative element by characterizing our results considering both the gender of the student and the gender of the parents. Chung and Zou (2023) distinguishes between the effects of maternal and paternal education on peers. According to the paper, there seems to be a stronger influence of peer mothers relative to that of peer fathers, due to the different roles played by mothers and fathers in family duties. In our study the parental peer effect involves both peers' fathers and mothers, with some evidence of gender symmetry, consistently with a role-model effect from peers' parents on human capital acquisition.

Another contribution of the paper relies on the exploration of non-linearities in peer effects, an aspect that –as remarked by Boucher et al. (2024) – has relevant policy implications but has been largely overlooked in the peer-effect literature, often solely based on linear-in-mean models. The above-mentioned finding that the effect peaks at intermediate levels of exposure suggests that, from a societal perspective aimed at increasing overall university enrollment, a certain degree of diversity in the educational and occupational background of peers' parents may be preferable to more polarized settings, where a few schools feature a high concentration of graduate parents while many others are predominantly composed of less educated families.

As a final contribution, the richness of our dataset based on administrative sources allows us to cover the entire population of Italian students, thereby improving external validity and substantially reducing concerns of sample selection in comparison with studies based on more limited survey data. Moreover, we can gain in terms of accuracy since we can follow the student over the years and combine the information collected in different points in times (secondary schools information are collected when the students are actually in secondary schools, and the same holds for tertiary education outcomes), overcoming possible issues with self-assessments over past of expected future experience. As regards the Italian context, Da Re (2025) investigates how the parental occupations of classmates influence students' decisions to enroll in specific high-school track. Our work represents the natural continuation of the analysis, as we investigate peer parents' effects at the next key educational transition, namely, the step from upper secondary school to university enrollment.

The rest of the paper is organized as follows. Section 2 presents the data and the main summary statistics. Section 3 describes the empirical strategy and discusses the identification issues. The main results are set out in Section 4. Existence of heterogeneous effects with respect to gender

is investigated in Section 5, while other dimensions of heterogeneity are explored in Section 6. Section 7 deals with the non-linearities in the estimated effect and the associated impliciations. Finally, Section 8 concludes.

2 Data and summary statistics

Our empirical analysis relies on two main sources of micro-level data. First, we exploited the Invalsi archives for 10^{th} grade students (i.e. second year of high school) in the school years from 2011-12 to 2017-18 to acquire the relevant information regarding a wide set of characteristics of high school students and of the occupational and educational characteristics of their parents. Table A1 shows the main characteristics of the INVALSI records. The second data source is the ANS dataset, a unique dataset that contains administrative records on students' academic careers and courses' supply (municipality, field, type, department, university) in all the Italian universities. We considered all students enrolled for the first time in an Italian university during the period 2010-2021, focusing on students between 18 and 20 years of age.[4]

Table 2.1 reports the most important students' and classes' characteristics, as well as the statistics of our main dependent variable (the enrollment rate in university).

As regards the students' characteristics, the INVALSI archives contain basic information about the students' gender, the nationality, the number of students retained in a class before 10^{th} grade and the number of early entrants in the compulsory school.[5] Moreover, it contains a wide set of educational outcomes of the 10^{th} grade students, namely: i) final mark in the lower secondary school leaving exam[6]; ii) the high school grade in Italian and mathematics acquired at the end of 9^{th} grade; iii) the overall average grade in Italian and mathematics in the first high-school term; iv) the INVALSI test scores in Italian and mathematics. In addition to information on individual students, the database also provides details about students belonging to the same high school class and the cohort of students who attended the same school.

As regard students' parents, the questionnaire in the Invalsi archives contains a set of questions on their economic, occupational and educational status. Descriptive statistics for all these parental characteristics are reported in Table A2. The original INVALSI codebook contained

[4]Using the freshman cohort rather than cohorts in subsequent years has the added advantage of not being subject to biases introduced by student failure and course repetition (Ciccone and Garcia-Fontes, 2015).

[5]In Italy, the practice of enrolling a child in primary school one year earlier than the standard age, so that the child starts first grade before turning six; as a result, these students are systematically younger than their classmates throughout compulsory schooling.

[6]The Italian "Esame di terza media" is the standardized final examination taken at the end of lower secondary school (grade 8, around age 13–14), which certifies completion of compulsory lower secondary education and determines admission to upper secondary school.

Table 2.1: Descriptive statistics: students' characteristics

	Mean	SD	Min.	Max.	N
Dependent variable					
Enrolled at University (%)	0.515	0.500	0	1	2,376,576
Students' characteristics					
Female (%)	0.506	0.500	0	1	2,266,991
Born in Italy (%)	0.937	0.243	0	1	2,137,323
On-time (%)	0.836	0.370	0	1	2,238,975
Early entrants (%)	0.012	0.108	0	1	2,238,975
Retained (%)	0.152	0.359	0	1	2,238,975
1st quad. grade - Ita	6.289	1.033	1	10	2,164,808
1st quad. grade - Mat	6.012	1.403	1	10	2,163,858
Italian State Exam (Maturità)	79.098	12.479	60	101	2,189,632
Academic School (%)	0.508	0.500	0	1	2,374,735
Classes' characteristics					
Female in class (%)	0.506	0.289	0	1	2,364,963
Early entrants in class (%)	0.012	0.038	0	1	2,356,845
Retained in class (%)	0.154	0.163	0	1	2,356,845
Born in Italy in class (%)	0.936	0.087	0	1	2,343,002
N. students in class	19.194	4.709	8	37	2,376,576
Cohort's characteristics					
Female in school (%)	0.506	0.236	0	1	2,375,782
Early entrants in school (%)	0.012	0.029	0	1	2,371,138
Retained in school (%)	0.155	0.136	0	1	2,371,138
Born in Italy in school (%)	0.937	0.061	0	1	2,370,704
N. students in school	130.846	78.100	8	497	2,376,576

Note: The table reports means, standard deviations, minima, maxima, and the number of non-missing observations for each variable. *Enrolled at University* is an indicator equal to one if the student is recorded as enrolling in an Italian university after high school in the ANS administrative records, and zero otherwise. *Female* and *Born in Italy* are binary indicators; *Retained*, *Early entrants*, and *On-time* describe students' schooling progression in high school. *1st quad. grade – Ita/Mat* are first-quadrimester grades on a 1–10 scale. *Italian State Exam (Maturità)* ranges from 60 to 100, with *100 e lode* coded as 101. Class-, school-, and cohort-level variables expressed in percent are computed as the share of students in the relevant class/school/cohort with the specified characteristic. Differences in the number of observations across variables reflect missing information in the underlying administrative sources.

ten detailed occupational categories referring to a wide range of labor market conditions, from unemployment to managerial and professional positions.[7] To enhance interpretability and facilitate their use in regression analyses, these categories were aggregated into a smaller set

[7]The original categorization is the following: 1) Unemployed; 2) Homemaker; 3)Executive / Manager; 4) Entrepreneur / Farm owner; 5) Employee professional / Freelance professional; 6) Self-employed worker; 7) Teacher / Clerical worker; 8) Manual worker / Laborer; 9) Retired / Pensioner. Retired individuals were not included in any macro-category because their occupational status does not reflect current labor market conditions.

of macro-groups reflecting key divisions in labor market position and socioeconomic standing. Specifically, we distinguished four main occupational statuses: not employed, blue-collar, qualified/white-collar, and self-employed.[8] Parental education levels were also recoded into the following categories: no upper secondary qualification, high school diploma, and university degree. Combined parental indicators were then constructed by taking the maximum value across the two parents: each dummy equals 1 if at least one parent belongs to a given category, and 0 otherwise. This approach captures the presence of specific educational or occupational characteristics within the household rather than focusing on a single parent. Additionally, a binary indicator for being born in Italy and quartiles of the ESCS index were included as proxies for parental nationality and economic background.

Starting from the education and professional information of the parents, and knowing which students belong to the same secondary school cohort, we were able to construct our main variable of interest: the share of the student's peers whose parents have a certain education or belong a certain profession. Table 2.2 reports the distribution of peers' parents by education and occupation. Almost half of students have peers whose parents have no upper-secondary diploma, about 52% have peers with parents holding a high school diploma, and 27% have peers with at least one parent holding a university degree. The share of an individual's peers who have at least one parent with a university-level education constitutes our main explanatory variable.

When parental occupational status is also considered, 38% of students have peers with non-employed parents, 35% have peers with parents in blue-collar occupations, and 49% have peers with parents in white-collar occupations.[9] The joint distribution of education and occupation, focusing in particular on parents with a university degree, shows that around 22% of peers' parents hold a degree but are not employed or employed as blue-collars. Another 73% of peers are graduated and are white collars. These combinations will be used in the subsequent analyses to highlight the importance of the friends' parents' occupation, in addition to their educational attainment.

The dependent variable is defined as the probability of enrolling in university within three years

[8]Individuals coded as not employed include both unemployed persons and homemakers, as both categories represent non-participation in the labor market. The blue-collar group is composed of manual workers (operai), typically associated with lower-skilled and lower-income occupations. The qualified/white-collar group includes employees and professionals requiring higher education or specific qualifications (e.g., managers, professionals, teachers, or clerical workers), while the self-employed category includes entrepreneurs, business owners, and independent workers.

[9]We exclude self-employed workers from the analysis, as this category constitutes a highly heterogeneous aggregate in our dataset — encompassing both manual occupations comparable to blue-collar work and occupations requiring higher education. This heterogeneity makes it difficult to classify self-employment as a proxy for either high or low human capital employment outcomes.

Table 2.2: Distribution of peer's parents by education and occupation

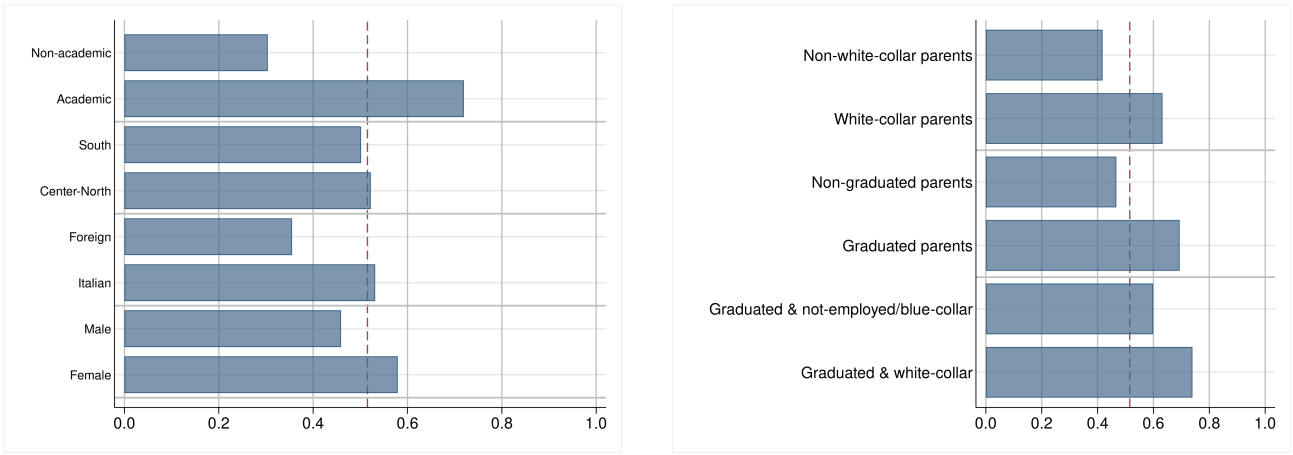
	Parents	Mothers	Fathers
Education (%)			
No diploma	49.0	34.9	40.3
Diploma	51.7	38.1	35.3
Graduates	27.5	20.7	18.9
Occupation (%)			
Not employed	38.0	36.6	4.4
Blue collar	35.2	18.4	26.8
White collar	49.1	33.3	37.0
Education & Occupation (%)			
Graduates and not employed	11.3	14.5	1.6
Graduates and blue collar	10.9	9.7	7.9
Graduates and white collar	73.1	67.1	73.5

In the subsection "Education & Occupation" the shares are calculated over the number of graduates. The residual category (graduates and self employed) is not displayed.

after obtaining a high school diploma. Approximately half of the students in the sample enrolled in university during the observation period, with this proportion remaining largely stable across cohorts. Figure 2.1 illustrates heterogeneity in enrollment patterns across individual, school, and family background characteristics.

Panel (a) focuses on individual and school characteristics. Enrollment rates are higher among women than men, among Italian nationals relative to non-nationals, and among graduates from academic high schools (licei) compared to other upper-secondary tracks. By contrast, differences between students residing in the Center–North and those in the South are relatively small. Panel (b) presents enrollment rates across parental background measuresEnrollment is higher among students whose parents are employed in white-collar occupations compared to those with non-white-collar parents, and among students with graduated parents relative to those from non-graduated families. When parental education is combined with labour-market status, we find that enrollment rates are lower among students whose graduated parents are either not employed or employed in blue-collar occupations, and higher among those with parents who are both highly educated and employed in white-collar jobs. Overall, the figure highlights a strong positive association between parental socio-economic standing and the likelihood of university enrollment.

Figure 2.1: University enrollment rates



(a) Schools' and students' characteristics

(b) Parents' characteristics

Notes. In both panels, bars report group means of the probability of enrolling in university within three years after high school. The red dashed vertical line indicates the overall sample mean. Categories are displayed in pairs and separated by light horizontal guide lines. Axes are standardized to facilitate comparisons across groups.

3 Estimation strategy

We follow the empirical approach originally developed in Hoxby (2000) that exploits the heterogeneity in peer exposure within school and across cohorts. A similar approach has been applied, among others, by Brenøe and Zölitz (2020), Carrell et al. (2018), Merlino et al. (2019), Modena et al. (2022) and Porreca et al. (2024). In doing so, we control for a number of factors that could introduce confounding elements, such as time-variant characteristic at the individual, class and school level.

More in detail, our linear probability model in its benchmark specification is as follows:

$$y_{i,s,c,t} = \alpha + \beta\, PEERS\_SHARE_{st}^{-i,H} + \gamma' \mathbf{X}_{i,s,c,t} + \theta' \mathbf{S}_{i,s,c,t} + \delta_s + \tau_t + \varepsilon_{i,s,c,t} \tag{1}$$

where $y_{i,s,c,t}$ is a dummy variable equal to 1 if individual i in high-school s, class c, year/cohort t is enrolled in university in the following three years.[10] The coefficient of interest is β. It is associated with $PEERS\_SHARE_{st}^{-i,H}$, measuring the share of individual i's peers who have at least one parent with a high (i.e., university-level) education. Peers are defined at the school level in order to avoid endogeneity issues related to class formation.

The vector $\mathbf{X_{i,s,c,t}}$ denotes control variables at the student level: gender, grade progression

[10]Notice that in our setting indexing by t is equivalent to indexing by cohort. The dummy is equal to 0 also if the individual did not complete the secondary school.

indicators (on-time, early attendant, retained student), attendance of nursery schools, being Italian native speaker. The vector also includes variables related to the student's family background: household socio-economic level (four classes based on quartiles), the mother's and father's educational and occupational status, and whether they are foreign-born. In order to more accurately account for the student's predetermined ability, we also include the average grade in the previous term and the associated percentile rank in the class.[11] Table B1 in the Appendix shows descriptive statistics of all the control variables.

As the identification occurs at the school level and exploits cross-cohort variation, it is important to include controls at the class level to account for compositional effects along this dimension. Therefore, the vector $\mathbf{S}$ includes the class size (and its square and cube), the peers' average grade in the previous term, and the class share of: female students, early entrants, retained students, foreign students (distinguishing between EU and extra-EU), students with foreign-born father and/or mother. The vector $\mathbf{S}$ also includes these time-varying shares computed at the school level, as well as the average class size, the school size (and its square and cube), and school-type fixed effects (academic, vocational, technical).

On top of that, τ_t and δ_s capture, respectively, time (cohort) fixed effects and school fixed effects. The former account for unobserved differences across cohorts over years, while the latter control for any time-invariant heterogeneity between schools (and hence also areas) and endogenous sorting into schools. In more saturated specifications of model (1), we allow for school-specific time trends τ_{ts} accounting for potential linear, quadratic or cubic trends that may peculiarly characterize each school from the others introducing a mechanical correlation between peers' exposure and enrollment probability.

By controlling for all these factors, we can evaluate parental effects across cohorts with a comparable school and class composition. This is important because, while the parental peer effect may still operate through exposure to mates, it is isolated from its possible influence in terms of observable features of school/class composition (such as average student ability, as proxied by peers' mean grades). Hence the estimated peer parental impact must be effective over and above these compositional mechanisms, and is possibly channeled through unobservable characteristics of peers.

We cluster the standard errors at the school level to account for any possible correlation in disturbances among cohorts of the same school that could possibly survive to the other controls.

[11] Results are robust to the use of other proxyies of student's ability, such as those based on the National Evaluation Program of Students' Achievement (NEPSA) promoted by Invalsi, the Italian education authority. A specific section in the Appendix explores different measures of students' ability and check for their correlations.

The extensive set of control variables – which we are able to include in the model thanks to the richness of our dataset – limits the possibility of bias introduced by unaccounted factors. A bias can arise if there are unaccounted factors correlated with both the peer exposure and the student's enrollment outcome. However, such a factor should simultaneously be time-varying (otherwise it would be swept out by school fixed effects) in a school-specific way uncorrelated with linear, quadratic or cubic trends (otherwise it would be cancelled out by the time fixed effects or the school-specific trends). Moreover, such a factor should work through channels not included in the extensive set of characteristics at the individual, class or school level which enter as control variables. While the absolute lack of such factors cannot be proven, it can be reasonably argued that the room for them is quite limited.

Following Modena et al. (2022) and Porreca et al. (2024), we provide suggestive evidence supporting the validity of the identification strategy. One of the main challenges to identification is dampening the strong correlation between own parents' education and that of peers' parents, which likely reflects a source of endogeneity. In order to see whether school and cohort fixed effects are able to do it, we regress our variable of interest (the share of peers' parents with a university degree) on a dummy for the same educational attainment of own parents. Results are reported in Table 3.1. Column (1) shows the strong and positive correlation in an unconditional setting. In column (2), where school and fixed effects are introduced, the coefficient goes down achieving slightly negative values. A negative coefficient can actually be consistent with a random assignment, as emphasized by Guryan et al. (2009): a negative relationship arises mechanically from the fact that any given student cannot be his/her own peer; consequently, the leave-one-student-out average will differ across students according to each student's own contribution to that average. Intuitively, a student with a graduate parent will mechanically have a slightly lower share of peers with graduated parents compared to any mate with no graduated parents. In order to correct for such a bias and following Guryan et al. (2009) and Porreca et al. (2024), we control for the average share of peers with graduated parents across cohorts within school. As expected, this augmented model brings about an upward correction in the coefficient, which becomes slightly positive (column 3). Adding the set of control variables does not change the result (columnn 4). When we consider our benchmark specification with a school-specific linear trend (column 5), the coefficients become statistically insignificant; allowing for different functional forms of the trend (i.e. quadratic or cubic, in columns 6 and 7, respectively) does not substantially change the results. Based on this evidence, we conclude that the coefficient's magnitude is very close to zero and negligible from both an economic and a statistical point of view. This is reassuring that, if any substantial peer effect is going to emerge, it will not be driven by the correlation with student's own parents.

Table 3.1: Share of peers with highly-educated parents and education of the student's parents

	Dep. var: Share of peers' with a parent holding a university degree						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Graduate Father	0.1065***	-0.0004***	0.0014***	0.0014***	0.0002	0.0003^{+}	0.0003^{+}
	(0.0028)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Graduate Mother	0.0944***	-0.0002	0.0016***	0.0015***	0.0001	0.0001	0.0000
	(0.0022)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
N	1,857,693	1,857,690	1,857,690	1,618,035	1,618,035	1,618,035	1,618,035
Adjusted R^2	0.151	0.920	0.920	0.923	0.944	0.944	0.944
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
School FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Guryan et al. (2009) correction			Yes	Yes	Yes	Yes	Yes
Controls				Yes	Yes	Yes	Yes
Trend					Linear	Quadratic	Cubic

Note: Standard errors clustered at the school level in parentheses:, $+ p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

While controlling for school and cohort fixed effects is proved to be effective in removing the correlation between the individual's parental educational attainment and that of their peers, a potential concern is that such controls may also remove a substantial portion of the variation in the variable of interest, thereby diminishing its explanatory power (Modena et al., 2022). However, as illustrated in Table 3.2, this is not the case: when we include the full set of fixed effects, the residual variation still accounts for more than one quarter of the original one. Whether this is enough to reliably estimate the peer effect is an empirical issue that we check in the next section. The evidence for the presence of peer effects can be considered stronger if it still emerges despite the substantial reduction in the available variation due to the inclusion of so many fixed effects.

Table B2 in the Appendix shows that, in addition to school and time fixed effects, it is important to control for compositional factor that may vary within school and across cohorts, while being correlated with the peers share with educated parents. For instance, and not surprisingly, a higher share of anticipatory (retained) peers is positively (negatively) associated with the peers' parental education. Interestingly, no such correlation does emerge with respect to the share of foreign born students, once school and cohort fixed effects are controlled for; conversely, there is a negative correlation with the female share.[12]

[12]While this result is not followed by a straightforward intuition, further inspection of data indicates that the negative coefficient of the female share is largely driven by academic high schools: it could reflect that, within this group of schools, the female share is higher in fields of study that are relatively more common among households where parents do not hold a university degree (e.g. language, human sciences, psycho-pedagogical high schools compared to scientific high schools; AlmaLaurea, 2022).

Table 3.2: Distribution of share of graduated peers' parents.

	Parents	Fathers	Mothers
Raw distribution			
Mean	0.274	0.189	0.206
Standard deviation	0.176	0.149	0.147
Net of year fixed effects			
Standard deviation	0.173	0.147	0.144
Net of school fixed effects			
Standard deviation	0.054	0.045	0.051
Net of school and year fixed effects			
Standard deviation	0.050	0.045	0.047
Net of linear trend,school and year fixed effects			
Standard deviation	0.043	0.039	0.040

Note:.

In further steps of the analysis, we refine the definition of the peer exposure. First, in Section 4.2 we look at the exposure to peers whose parents do not have a university degree, distinguishing between those with a medium education – a high-school diploma (defined as $PEERS\_SHARE_{st}^{-i,M}$) – and the less educated ones ($PEERS\_SHARE_{st}^{-i,L}$). Next, in Section 4.3 we match education with actual labour market condition distinguishing between "unfavourable" outcomes ($PEERS\_SHARE_{st}^{-i,H,\underline{J}}$) and job outcomes that are more likely to be consistent with their educational attainment ($PEERS\_SHARE_{st}^{-i,H,\overline{J}}$). In Section 5 we explore the gender dimension measuring the peers' exposure gender-wise, with respect to the sex of both the student i and the parents.[13]

When considering occupation, a potential concern of reverse causality may be raised as parents may adjust their occupational choices in response to their children's educational trajectories. However, we argue that, if present, such effects are likely to be of minor order in our setting for two main reasons. First, our analysis exploits the occupational status of peers' parents, rather than that of students' own parents, which substantially weakens any direct feedback mechanism. Second, occupational categories are defined at a highly aggregated level, so any relevant adjustment would need to occur at the extensive margin of labour market participation or involve major transitions between blue- and white-collar occupations, rather than decisions

[13]More specifically, we estimate model (1) for the separate sub-samples of female and male students, obtaining estimates of β_g^H and β_b^H, where g and b denotes girls and boys, respectively. Then, we compute the exposure restricted to either fathers or mothers: $PEERS\_SHARE_{st}^{-i,H,fa}$, $PEERS\_SHARE_{st}^{-i,H,mo}$ and we obtain the estimate of its impact for the overall sample and for both subsamples of boys and girls: $\beta_g^{H,mo}$; $\beta_g^{H,fa}$; $\beta_b^{H,mo}$; and $\beta_b^{H,fa}$.

such as transitions between full-time and part-time work or career progression. Effects on the extensive margin of labour force participation due to child-care duties are typically more pronounced when children are younger, whereas the educational choice we focus on is made in the final year of high school, when students are already young adults.

4 Main Results

4.1 The effect of peers' high parental education

Table 4.1 reports the results for the estimates of model (1), showing the the effect of the share of peers whose parents are highly educated on the likelihood of university enrollment.

Table 4.1: Effect of peer's highly-educated parents on university enrollment

	(1)	(2)	(3)	(4)	(5)	(6)
	Dep. variable: likelihood of enrolling in university					
$PEERS\_SHARE^{-i,H}$	0.089***	0.082***	0.081***	0.063***	0.071***	0.077***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
N	2,007,606	1,618,094	1,617,995	1,617,995	1,617,995	1,617,995
adj. R^2	0.282	0.332	0.333	0.336	0.336	0.335
School and Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual-level controls		Yes	Yes	Yes	Yes	Yes
School- and class-level controls			Yes	Yes	Yes	Yes
Sample	Full	Full	Full	Full	Full	Full
Trends				Linear	Quadratic	Cubic
Mean of Y	0.529	0.547	0.547	0.547	0.547	0.547
Mean of X	0.274	0.278	0.278	0.278	0.278	0.278
Std. Dev. of X	0.176	0.177	0.177	0.177	0.177	0.177

Note: $PEERS\_SHARE^{-i,H}$ is the share of peers with a high parental education, computed referred to any parent. The table reports in the estimates of model (1) in column (1).
Standard errors clustered at the school level in parentheses:, + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We consider a sequence of specifications. Column (1) includes only school and cohort fixed effects. In column (2), we add individual-level control variables, while in column (3) we further account for the other control variables at the school and class level. The estimated coefficient decreases only slightly, from 0.089 to 0.081 from columns (1) to (3), indicating that the positive effect still holds when comparing otherwise similar individuals and schools. In columns (4) to (6) we further saturate the model by allowing for possible school-specific time trend, considering alternative functional forms: linear (col. (4)), quadratic (col. (5)), or cubic (col. (6)). Even under these more demanding specifications, the educational background of peers' parents continues to exert a positive and statistically significant effect students' enrollment decisions.

In the remainder of the analysis, we take the most conservative specification – namely, the model with school-specific linear trend in col. (4) – as benchmark.

The benchmark estimate indicates that a 1 percentage point (pp) increase in the share of peers whose parents hold a university degree raises the dependent variable by 0.06 pp. When considering a one-standard deviation increase in the explanatory variable, this implies a rise by 1.0 pp on the probability of university enrollment, relative to a sample mean of 55%.

The magnitude of the peer effect can also be compared with the effect of own parental education. Evaluated at the median peer-group size, the estimates imply that a 10% increase in the number of peers with a graduate parent increases the probability of university enrolment by an amount equivalent to about nearly one fifth (18%) of the direct effect of having a graduate father.[14]

In terms of unitary impact (i.e, the impact brought about by adding just one more peer) and keeping the median group size as reference, the magnitude represents about the 2% of the direct effect of father's education. Relative to the literature, this magnitude is consistent with estimates obtained in settings with strong identification and rich controls (Feld and Zölitz, 2017; Chung and Zou, 2023). The result aligns with the consensus that the peer effects on educational choice are positive and, while quantitatively modest compared to family background, they should not be considered as negligible for several reasons. First, own parental education is widely recognized as one of the strongest predictors of educational attainment: consequently, any contextual effect – such as peer composition – would be expected to be substantially smaller in comparison. Second, the estimate is obtained under a highly conservative specification that includes rich individual- and school-level controls as well as school-specific time trends: that the peer effect remains positive and statistically significant even under these demanding assumptions supports its substantive relevance. Third, the effect captures an indirect spillover channel operating net of compositional factors: effects of this nature are inherently second-order and therefore expected to be smaller in magnitude. Nonetheless, their presence is meaningful, particularly because peer composition is potentially more amenable to policy interventions than family background.

[14]This back-of-the-envelope computation is performed by scaling the peer-effect coefficient by the median size of the peer group and relating the implied effect of a 10% increase in peers with a graduate parent to the coefficient of the control dummy variable for having a graduate father. The relative magnitude is slightly larger when compared to the effect of having a graduate mother. Averaging across the two coefficients of own mother's and father's education, the estimated peer effect corresponds to about one fourth of the direct effect of parental education.

4.2 The effect of peers' with less educated parents

We next allow peers' parental education to vary across levels to test whether peer effects operate symmetrically and whether exposure to moderately educated parents is sufficient to generate comparable effects.

Table 4.2 reports estimates from the same benchmark specification, replacing $PEERS\_SHARE^{-i,H}$ with the share of peers whose parents did not complete high school ($PEERS\_SHARE^{-i,L}$), hold a high-school diploma but not a university degree ($PEERS\_SHARE^{-i,M}$).

Table 4.2: Evidence on university enrollment. The role of less educated parents.

	Dep. variable: Enrollment in university		
	(1)	(2)	(3)
Share of peers' parental education defined as:	no high-school diploma	high-school diploma	university degree
$PEERS\_SHARE^{-i,L}$	-0.069***		
	(0.008)		
$PEERS\_SHARE^{-i,M}$		0.025***	
		(0.008)	
$PEERS\_SHARE^{-i,H}$			0.063***
			(0.010)
N	1,617,995	1,617,995	1,617,995
adj. R^2	0.336	0.336	0.336
School and Cohort FE	Yes	Yes	Yes
Individual-level controls	Yes	Yes	Yes
School-level controls	Yes	Yes	Yes
Linear trend	Yes	Yes	Yes
Sample	Full	Full	Full
Mean of Y	0.547	0.547	0.547
Mean of X	0.487	0.519	0.278
Std. Dev. of X	0.204	0.114	0.177

Note: Standard errors clustered at the school level in parentheses: + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table reports in the estimates of model (1) in column (3). In column (1) the share is computed considering the peers' parents with less than high-school education. In column (2) the share is computed considering the peers' parents holding a high-school degree but not a university degree.

A higher share of peers whose parents did not complete high school is associated with a significantly lower probability of university enrollment: a 1 pp increase in $PEERS\_SHARE^{-i,L}$ reduces enrollment by about 0.069 pp (column (1)). For exposure to peers whose parents hold a high-school diploma ($PEERS\_SHARE^{-i,M}$), the effect is positive but markedly smaller—nearly

two thirds lower—than the benchmark with graduate parents (column 3). These findings suggest that the peer effect associated to parental education increases in the educational level of peers' parents. In other words, it is not simply a matter of exposure to some moderate level of education, as it could have been concluded if the coefficients of columns (2) and (3) were of similar in magnitude.

This analysis supports that it is the exposure to high-educated (i.e., graduate) parents of peers that mostly matters. This pattern implies that the cultural and informational capital transmitted through school peer networks depends critically on the availability of high-education role models, not just the absence of educational disadvantage. These results motivate the next step: assessing whether education *per se* is sufficient, or whether effects are amplified when high education is coupled with favorable occupational outcomes.

4.3 Beyond education: the role of peers' parental occupation

We finally examine whether the effect of exposure to peers' highly educated parents depends on their labor-market outcomes. Observing highly educated parents in low-status jobs (or out of employment) may transmit different signals than observing highly educated parents in occupations aligned with their credentials. We therefore split the peer measure into two components: (i) highly educated parents who are not employed or are employed in blue-collar occupations ($PEERS\_SHARE^{-i,H,\underline{J}}$), and (ii) highly educated parents in white-collar occupations ($PEERS\_SHARE^{-i,H,\overline{J}}$), and estimate the benchmark specification for each.

Table 4.3 shows that the influence of peers' highly educated parents on university enrollment significantly varies by occupational status. While column (1) reports our baseline specification as a benchmark (i.e., irrespective of occupational outcome), in column (2) we focus on the exposure to peers with high education level but an unfavourable occupational outcome ($PEERS\_SHARE^{-i,H,\underline{J}}$). We define the latter as being not employed or being employed as a blue-collar, since both situations represent a under utilization of the human capital acquired through tertiary education.[15] We find that in this case the impact is not statistically different from zero. This suggests that a high educational attainment alone is not sufficient to generate aspirational effects.

In contrast, there is a positive and highly significant effect when the computation of the share requires that a high education is matched with being employed in a white-collar job ($PEERS\_SHARE^{-i,H,\overline{J}}$; column (3)). The magnitude of this effect, equal to 0.85 in the point

[15]We refer to under-usage of human capital in the labour market, leaving aside any possible beneficial role of this human capital in other fields, like child-rearing.

estimate, is larger than in the benchmark model in column (1), suggesting that the positive influence of peers' highly educated parents is strengthened when combined with a visible adequate occupational outcome. While we cannot rule out the possibility of over-qualified workers for their jobs, still column (3) provides evidence of an enhanced effect when clearer unsuccessful outcomes for graduates such as unemployment or physical and operational jobs are excluded.

Table 4.3: High educated peers' parents and occupation

	Dep.variable: Enrollment in university		
	(1)	(2)	(3)
Share of peers' highly educated parents with occupation:	All	Not empl./Blue-Coll.	White-Collar
$PEERS\_SHARE^{-i,H}$	0.063***		
	(0.010)		
$PEERS\_SHARE^{-i,H,\underline{J}}$		0.028	
		(0.018)	
$PEERS\_SHARE^{-i,H,\overline{J}}$			0.085***
			(0.011)
N	1,617,995	1,617,987	1,617,987
adj. R^2	0.336	0.336	0.336
School and Cohort FE	Yes	Yes	Yes
Individual-level controls	Yes	Yes	Yes
School-level controls	Yes	Yes	Yes
Linear trend	Yes	Yes	Yes
Sample	Full	Full	Full
Mean of Y	0.547	0.547	0.547
Mean of X	0.278	0.060	0.204
Std. Dev. of X	0.177	0.038	0.159

Note: Standard errors clustered at the school level in parentheses: + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table reports in the estimates of model (1) in column (1). In column (2) the share is computed considering the joint condition of university degree and being in a blue-collar occupation or no employment. In column (3) the share is computed considering the joint condition of university degree and being in a white-collar occupation.

These results offer a combined perspective that sheds light on how role-model influences stem from socioeconomic signals that are broader than just academic credentials. The findings suggest that it is actually the inherently joint combination of education and professional career that matter in shaping the peer effect.

5 Gender heterogeneity

As noted in prior literature, the effect of role models in shaping individual aspirations and behaviors can be gender specific (Chung and Zou, 2023). In particular, the influence exerted

by mothers and fathers may differ, reflecting distinct social roles, expectations, and forms of engagement with children. At the same time, students may respond differently to role models depending on their own gender, with same-gender role models often exerting a stronger or more salient effect. For instance, female students may be more influenced by the presence or characteristics of mothers among their peers' parents, while male students may respond more to fathers. These considerations suggest the examine heterogeneity in peer effects along a gender perspective, in order to better understand how social exposure shapes educational or behavioral outcomes.

Therefore, we begin by distinguishing between student genders. The results reported in Table 5.1 indicate that the share of peers with highly educated parents positively affects the likelihood of university enrollment for both female and male students (columns (2) and (3) respectively, whilst col. (1) replicates the result on the overall sample). Specifically, a one percentage point increase in the share of peers whose parents hold a university degree raises the probability of enrollment by 0.053 percentage points for females and 0.061 for males (columns 2 and 3).

Then, we complement the analysis by distinguishing peers' parents between mothers and fathers, again for the overall sample (column 4), for the sample of female students only (column 5), and for the one of male students only (column 6). We find that the share of graduates among both mothers and fathers of peers are positively associated with university enrollment, and the difference between the two is not statistically significant (column 4). This pattern holds for both female (column 5) and male students (column 6). This suggests that the influence of highly educated parents on students' outcomes is not too dissimilar with respect to the parent's gender. However, the point estimates hint that their relative influence may differ by student's gender. The effect of highly educated fathers appears somewhat stronger for male students, while the coefficient for peers' mothers' education is slightly larger among female students, thus suggesting that same-gender identification may play a role.

Overall, these results point to nuanced gender-specific mechanisms in the social transmission of educational aspirations, suggesting a possible role model channel, whereby exposure to highly educated parents of the same gender may exert a stronger effect in shaping expectations and the perceived value of higher education.

In Table 5.2 we go more in depth into this issue by examining whether the results by occupations are gender-based, considering again the gender of both the parents and the students [16]. The first

[16]Motivated by the higher incidence of non-employment among highly educated mothers, we perform additional robustness checks in which bad occupational outcomes are defined solely by unemployment, excluding blue-collar employment. The estimates are very similar to those reported in Table 5.2 and do not affect the main conclusions. Results are available upon request.

Table 5.1: Evidence on university enrollment. Gender effect.

	Dep. variable: likelihood of enrolling in university					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	All students	Female students	Male students	All students	Female students	Male students
$PEERS\_SHARE^{-i,H}$	0.063***	0.053***	0.061***			
	(0.010)	(0.013)	(0.013)			
$PEERS\_SHARE^{-i,H,fa}$				0.042***	0.034**	0.051***
				(0.012)	(0.016)	(0.016)
$PEERS\_SHARE^{-i,H,mo}$				0.051***	0.050***	0.039**
				(0.012)	(0.016)	(0.015)
N	1,617,995	842,077	775,706	1,617,983	842,072	775,699
adj. R^2	0.333	0.294	0.361	0.333	0.294	0.361
School and Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual-level controls	Yes	Yes	Yes	Yes	Yes	Yes
School-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Linear trend	Yes	Yes	Yes	Yes	Yes	Yes
Mean of X	0.278	0.291	0.265			
Std. Dev. of X	0.177	0.175	0.177			
Mean of X - Father				0.191	0.201	0.181
Std. Dev. of X - Father				0.149	0.148	0.149
Mean of X - Mother				0.209	0.219	0.199
Std. Dev. of X - Mother				0.148	0.147	0.147

Note: Standard errors clustered at the school level in parentheses: + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
The share of peers with a high parental education is computed referred to: any parent ($PEERS\_SHARE^{-i,H}$, as in the benchmark), only fathers ($PEERS\_SHARE^{-i,H,fa}$) and only mothers ($PEERS\_SHARE^{-i,H,mo}$). The regressions are run on the all sample in columns (1) and (4); considering the subsample made of female students only in columns (2) and (5); considering the subsample made of male students only in columns (3) and (6).

three columns consider the high education coupled with a bad economic outcome, distinguishing between parents' gender and carrying out the estimates on the whole sample of students (col. (1)), on the female sub-sample (col. (2)), and on the male sub-sample (col. (3)). The results confirm the main finding that: i) when exposure to highly educated parents is coupled with an unsuccessful outcome in the labour market, the positive peer effect disappears; ii) the suggestive presence of a role model effect found in Table 5.1 is confirmed also when we also take occupation into account.

In the remaining columns of Table 5.2 we move to the exposure to peers' graduate parents combined with an occupational outcome that is more in line with the education level achieved.

Table 5.2: High educated peers' fathers and mothers and occupation.

	Dep.variable: likelihood of enrolling in university					
	(1)	(2)	(3)	(4)	(5)	(6)
Occupation:	Not employed or blue collar			Employed as white-collar		
Sample:	All stud.	Female st.	Male stud.	All stud.	Female st.	Male stud.
$PEERS\_SHARE^{-i,H,fa,\underline{J}}$	-0.010	-0.069+	0.046			
	(0.030)	(0.041)	(0.039)			
$PEERS\_SHARE^{-i,H,mo,\underline{J}}$	0.032+	0.019	0.037			
	(0.019)	(0.026)	(0.024)			
$PEERS\_SHARE^{-i,H,fa,\overline{J}}$				0.055***	0.047**	0.062***
				(0.013)	(0.017)	(0.018)
$PEERS\_SHARE^{-i,H,mo,\overline{J}}$				0.070***	0.073***	0.052***
				(0.014)	(0.018)	(0.018)
N	1,617,971	842,065	775,694	1,617,971	842,065	775,694
adj. R^2	0.336	0.297	0.364	0.336	0.297	0.364
School and Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual-level controls	Yes	Yes	Yes	Yes	Yes	Yes
School-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Linear trend	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Y	0.485	0.485	0.485	0.485	0.485	0.485
Mean of X - Father	0.017	0.017	0.017	0.141	0.150	0.131
Std. Dev. of X - Father	0.019	0.018	0.019	0.129	0.128	0.128
Mean of X - Mother	0.050	0.051	0.049	0.141	0.150	0.132
Std. Dev. of X - Mother	0.035	0.035	0.036	0.121	0.121	0.120

Note: Standard errors clustered at the school level in parentheses: + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
The share of peers with a high parental education is computed referred to: fathers and mothers with either unfavorable employment outcomes ($PEERS\_SHARE^{-i,H,fa,\underline{J}}$ and $PEERS\_SHARE^{-i,H,mo,\underline{J}}$, respectively), or with white collar occupations. The regressions are run on the all sample in columns (1) and (4); considering the subsample made of female students only in columns (2) and (5); considering the subsample made of male students only in columns (3) and (6).

It can be observed that the coefficients are positive, statistically significant and higher in magnitude than their corresponding values in Table 5.1 (columns (4) to (6)). This confirm that the finding that the parental peers effect is strengthened when education and occupation are jointly considered is confirmed across both genders of parents and students.

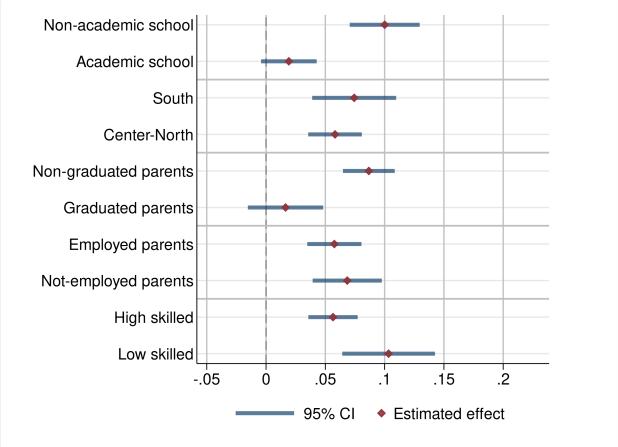
6 Other dimensions of heterogeneity

We investigate whether the effect of peers' parental background varies systematically across students' characteristics, family environments, and institutional contexts. Specifically, we estimate heterogeneous effects by school type, geographical area, parents' education and occupation, as well as skill composition. This approach allows us to assess whether peer effects differ across

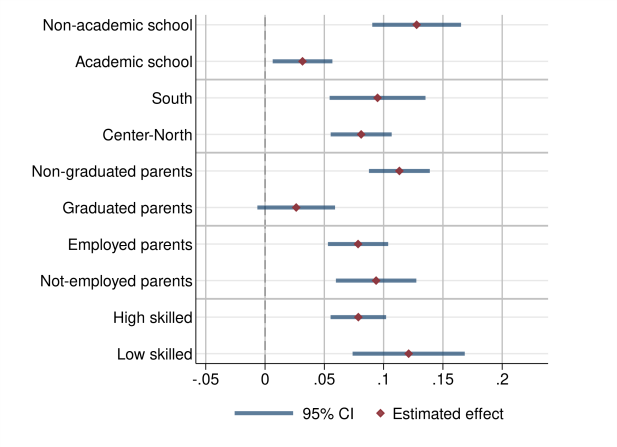
socio-demographic groups that are characterized by different baseline propensities to enroll in university.

Figure 6.1 reports the estimated coefficients and 95% confidence intervals for these subgroups. Panel (a) considers peers' parental background measured solely by parental education, while panel (b) focuses on a more restrictive definition that combines high parental education with employment in a white-collar occupation. Across both panels, the estimates reveal substantial heterogeneity along several dimensions.

Figure 6.1: Heterogeneous effects of peers' parental background



(a) Graduated peers' parents



(b) Graduated peers' parents in white-collar occupations

Notes. The dependent variable is the likelihood of enrolling in university. In panel (a), the independent variable is the share of peers with at least one parent holding a tertiary degree. In panel (b), the independent variable is the share of peers with at least one parent holding a tertiary degree and employed in a white-collar occupation. All specifications control for baseline individual and school characteristics. Error bars represent 95% confidence intervals.

A first robust pattern concerns school type. The effect of peers' parental background is markedly larger for students enrolled in non-academic schools relative to those attending academic tracks. Similarly, students whose own parents do not hold a university degree exhibit a stronger response to exposure to peers with advantaged parental backgrounds. These patterns suggest that peer effects are more pronounced in environments where the average propensity to pursue higher education is lower. In such contexts—such as non-academic schools or families without a university tradition—information and signals conveyed by peers' family backgrounds appear to play a more salient role in shaping educational aspirations.

Importantly, these heterogeneities persist when the peer measure is refined to capture both parental education and occupational status, as shown in panel (b). If anything, the estimated effects are systematically larger when peers are defined as having parents who are not only

highly educated but also employed in white-collar occupations. This finding suggests that peers' parental background operates not merely through educational attainment per se, but through a broader bundle of socio-economic characteristics that likely convey stronger signals about the returns to higher education, its attainability, and its compatibility with future labor market outcomes.

Taken together, the evidence indicates that peer effects are amplified when peers embody a more salient and visible form of socio-economic advantage, and when students are embedded in contexts where higher education is not the prevailing norm. In these settings, peers with highly educated and occupationally successful parents may function as particularly influential reference points, reinforcing aspirations toward university enrollment.

Finally, we also examine heterogeneous effects by gender. Overall, we do not detect statistically significant differences between males and females within any of the heterogeneity dimensions considered.[17]

7 Non linearities

As common in the literature, our estimates rely on a linear specification, thus implicitly assuming constant returns or a linear-in-mean effect. However, as emphasized by Boucher et al. (2024), peer effects can be non-linear and accounting for non-linearities is important to avoid possibly misleading policy implications. Knowing whether the impact is constant or exhibits increasing/decreasing returns might be valuable for assessing how the distribution of peers across schools influences the overall number of students pursuing high levels of education, thus suggesting a potential role for policy in determining the optimal mix of students. For instance, assuming as given the total number of highly educated parents, under decreasing returns a polarized distribution (where high-educated parents are concentrated in few schools) would be less efficient than a distribution in which they are more uniformly distributed across schools. The opposite would hold under increasing returns, while under constant returns (a truly linear effect) it would be less relevant studying how the peers' parental background is distributed.[18]

In order to study whether the effect of peers' parental education is non-linear, we adopt a non-parametric approach. More specifically, we modify model (1) and let the effect of the share of peers vary according to ten classes of the variable distribution, defined by its year-by-year deciles.[19] The share of peers refers to peers with a highly educated parent with better

[17] Results are available upon request.

[18] Under constant returns, any redistribution would have mutually offsetting effects.

[19] We compute deciles year by year rather than on the whole time interval to account for macro trends on the

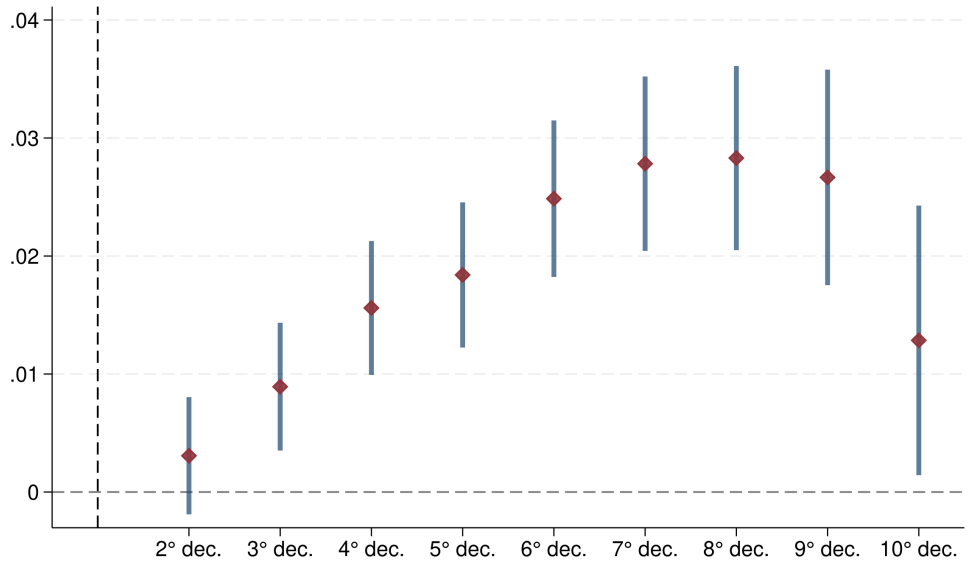
occupational outcomes ($PEERS\_SHARE^{-i,H,\bar{J}}$):

$$y_{i,s,c,t} = \alpha + \sum_{q=2}^{10} \beta_q^F \mathbb{D}_{qst}^{-i,H,\bar{J}} + \gamma' \mathbf{X}_{i,s,c,t} + \theta' \mathbf{S}_{i,s,c,t} + \delta_s + \tau_t + \varepsilon_{i,s,c,t} \tag{2}$$

where $\mathbb{D}_{qst}^{-i,H,\bar{J}}$ is a dummy variable equal to 1 if $PEERS\_SHARE_{st}^{-i,H,\bar{J}}$ belongs to qth decile of its distribution in year t. Figure B1 in the Appendix reports the decile levels across years. All the β_q are to be interpreted in relative terms to the effect on the first group, which is omitted to avoid perfect collinearity.

The results of model are (2) are graphically shown in Figure 7.1. While for the two lowest tenths the effect is similar, at higher levels the impact significantly increases. However, at the highest deciles the impact decreases.

Figure 7.1: Non linear effects of peers' parental education.



This evidence suggests that returns are not constant and that the peer effect is non-linear. On the one hand, there is a minimum level of the share below which small improvements are scarcely relevant. On the other hand, at high levels of the share, any further increase provides a smaller benefit.

This finding has important policy implications as it suggests that – in order to enhance the overall likelihood of enrolling at university – it would be preferable to avoid highly unequal or

share of highly educated population.

"segregated" equilibria in which are predominant schools with a polarized incidence of parents with a high educational background and good occupational outcomes. Situations where there is a greater variety in the parental background appears to exert a more beneficial impact on the overall likelihood to enroll in university. These parental characteristics are easier and feasible to observe with respect to other features of peers, such as their enrollment propensity (which is observed only later and can in turn be endogenously affected).

8 Concluding remarks

In this paper we have investigated the influence of peers' parental education and occupation on young individuals' decisions to pursue university education. The analysis draws upon a unique dataset that enables us to follow the same individuals from high school through university enrolment, incorporating detailed information on their performance and socio-economic background, as well as that of their peers, alongside a range of contextual variables at both the school and class levels. In order to overcome the typical identification issues in peer effect assessment, we have followed an approach à la Hoxby (2000) that exploits within-school cross-cohort variation in peers' characteristics. The richness of our dataset allows ut to control for potential confounding factors related to individual attributes and the associated sources of endogeneity (e.g.: sorting, homophily), compositional effects at the school or class level, as well as possible temporal trends.

Our findings suggest that peers' parents during adolescence play a crucial role in shaping students' educational choices. Specifically, peers' parental education influences university enrollment, but its impact significantly varies by occupational status. Low-educated parents reduce enrollment likelihood across all occupational groups, whereas highly educated parents only have a positive effect when paired with high-status or self-employed occupations. This means that the education level of the peers' parents matters, but that it is not enough in order to completely capture the effect.

An important policy implication of our findings is that increasing the average educational attainment in the population – by expanding the share of university graduates – generates significant second-round effects. Beyond the direct enhancement of current human capital levels, it also fosters human capital accumulation among the younger generations. Importantly, we show that this latter effect does not solely operates through the direct influence of parents on their own children, but also through a peer effect mechanism that impacts their children's classmates during high school. In addition to these dynamic effects, our analysis also provides another insightful policy implication. From a standpoint focused on boosting university enrolment, a

moderate level of diversity in peers' parental education may be more beneficial than highly polarized contexts, where some schools concentrate graduate parents while others are largely composed of less educated families.

Further promising lines of research could build upon the present analysis to deepen the understanding of peer effects driven by parental education. For instance, future studies might explore whether and how these effects persist over time, influence the choice of field of study, shape academic performance during university, and affect the transition to the labor market.

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Appendix

Descriptive statistics

Table A1: Summary statistics on INVALSI data by school year

Variable	2011–12	2012–13	2013–14	2014–15	2015–16	2016–17	2017–18
Aggregate values							
Students	278454	492966	495969	319124	481784	507968	524597
INVALSI records	244884	467326	475983	233205	363754	392887	488730
Response rate (%)	0.879	0.947	0.959	0.730	0.755	0.773	0.931
N. schools	3503	6050	6069	4450	5948	6146	6222
Cohort size	79.49	81.48	81.72	71.71	80.99	82.65	84.31
Distribution across school typologies (%)							
Academic schools (*Licei*)							
Num. schools	0.46	0.45	0.45	0.47	0.45	0.45	0.45
Students	0.50	0.49	0.48	0.49	0.49	0.50	0.51
INVALSI records	0.51	0.50	0.48	0.52	0.52	0.53	0.53
Non-Academic: Professional							
Num. schools	0.21	0.22	0.22	0.21	0.22	0.22	0.22
Students	0.19	0.19	0.20	0.19	0.20	0.19	0.18
INVALSI records	0.17	0.19	0.20	0.17	0.17	0.16	0.17
Non-Academic: Technical							
Num. schools	0.32	0.33	0.34	0.32	0.33	0.33	0.33
Students	0.32	0.32	0.32	0.31	0.32	0.31	0.30
INVALSI records	0.31	0.31	0.32	0.31	0.31	0.31	0.30

The average cohort size refers to the number of 10th grade students per school.
The response rate is calculated as the ratio between the theoretical number of students and the number of INVALSI records.

Table A2: Descriptive statistics: parents' occupational and educational characteristics

	Mean	SD	Min. value	Max. value	Num. of obs.
Fathers' characteristics (%)					
Born in Italy	0.891	0.312	0	1	2,099,558
Education:					
High school dropout	0.403	0.490	0	1	1,884,772
High school diploma	0.353	0.478	0	1	1,884,772
Graduated	0.189	0.392	0	1	1,884,772
Occupation:					
Not employed	0.044	0.204	0	1	1,987,082
Self-employed	0.294	0.456	0	1	1,987,082
Blue collar	0.268	0.443	0	1	1,987,082
White collar	0.370	0.483	0	1	1,987,082
Mothers' characteristics (%)					
Born in Italy	0.870	0.336	0	1	2,105,866
Education:					
High school dropout	0.349	0.477	0	1	1,944,378
High school diploma	0.381	0.486	0	1	1,944,378
Graduated	0.207	0.405	0	1	1,944,378
Occupation:					
Not employed	0.366	0.482	0	1	2,039,519
Self-employed	0.114	0.317	0	1	2,039,519
Blue-collar	0.184	0.388	0	1	2,039,519
White-collar	0.333	0.471	0	1	2,039,519
Parents' characteristics (%)					
Born in Italy	0.916	0.277	0	1	2,109,120
Education:					
High school dropout	0.490	0.500	0	1	1,989,544
High school diploma	0.517	0.500	0	1	1,989,544
Graduated	0.275	0.446	0	1	1,989,544
Occupation:					
Not employed	0.380	0.485	0	1	2,077,500
Self-employed	0.331	0.471	0	1	2,077,500
Blue-Collar	0.352	0.477	0	1	2,077,500
White-collar	0.491	0.500	0	1	2,077,500

Note: Variables in this table are dummies,and hence defined either with 0 or 1. Values pertaining to the occupational characteristics are recoded from a more granular definition. Educational outcomes do not include the category 'Post high school diploma'. The section that refers to the parents' characteristics refers to the distributional features possessed by at least one parent for each student.

Different measures of students' scores

Because prior achievement is a strong predictor of university enrollment and is likely correlated with the type of peers students are exposed to through sorting across schools, tracks, or classes, controlling for pre-existing educational attainment helps mitigate omitted-variable bias and makes students more comparable at baseline. Among the different measures reported in the questionnaire, we use the previous-semester grade (first semester of the second year of high school) as our preferred proxy for prior ability because it maximizes sample size and is measured sufficiently early that peer influences on later educational choices are plausibly less fully formed than at later points (e.g., the INVALSI tests administered in the second term of the same year). While an ideally predetermined measure would be the junior school exam (taken before high school entry and therefore before class composition is realized), its availability for fewer cohorts would substantially reduce the estimation sample; reassuringly, specifications using the junior school exam (and other alternative attainment controls) yield very similar peer-effect estimates. Table A2 reports the main distributional features of those variables, as well as their availability across different school years.

Table A3: Main distributional features of students' outcomes

Panel A: Descriptive statistics

	Mean	Std. dev.	Min	Median	Max	N
Prev. year grade	6.83	0.96	4.00	6.50	10.00	1,714,742
Prev. semester grade	6.15	1.07	1.00	6.00	10.00	2,168,899
Junior School Exam	7.95	1.31	6.00	8.00	11.00	1,700,133
Invalsi - pu score	55.75	17.58	0.00	56.64	100.00	1,842,585
Invalsi - wle score	204.63	39.05	-84.83	205.52	408.20	2,237,889

Panel B: Number of observations by school year

	2011–12	2012–13	2013–14	2014–15	2015–16	2016–17	2017–18
Prev. year grade	0	0	372,441	246,232	340,100	372,120	383,849
Prev. semester grade	100,667	356,467	360,889	248,152	337,519	381,307	383,898
Junior School Exam	0	0	371,355	245,667	339,318	371,848	371,945
Invalsi - pu score	102,554	374,196	374,638	254,411	347,053	389,733	0
Invalsi - wle score	99,170	374,196	374,638	254,411	347,053	389,733	398,688

Note: Grades are on a 1–10 scale. The Junior School Exam grade may include the distinction lode (Italian "cum laude") awarded to the best-performing students; grades of *10 e lode* are recoded as 11. INVALSI scores are standardized test metrics. Panel B reports availability in the administrative archives; zeros indicate years in which the measure is not observed.

Finally, the pairwise correlations shown in Table A4 indicate that the attainment measures capture a common underlying dimension of academic ability (moderate correlations around 0.4–0.7 across most pairs), while the two INVALSI metrics are almost collinear.

Table A4: Correlation of different measures of students' outcomes

	Prev. year grade	Prev. semester grade	Junior School Exam	Invalsi - pu score	Invalsi - wle score
Prev. year grade	1.00	-	-	-	-
Prev. semester grade	0.67	1.00	-	-	-
Junior School Exam	0.56	0.50	1.00	-	-
Invalsi - pu score	0.38	0.43	0.54	1.00	-
Invalsi - wle score	0.37	0.43	0.53	0.96	1.00

Note: Entries report Pearson correlation coefficients. Correlations are computed on the common sample of students with non-missing information for all variables shown (listwise deletion). Hyphens denote redundant cells (the matrix is symmetric).

Additional figures and tables

Figure B1: Distribution of peers' high-educated and white-collar parents

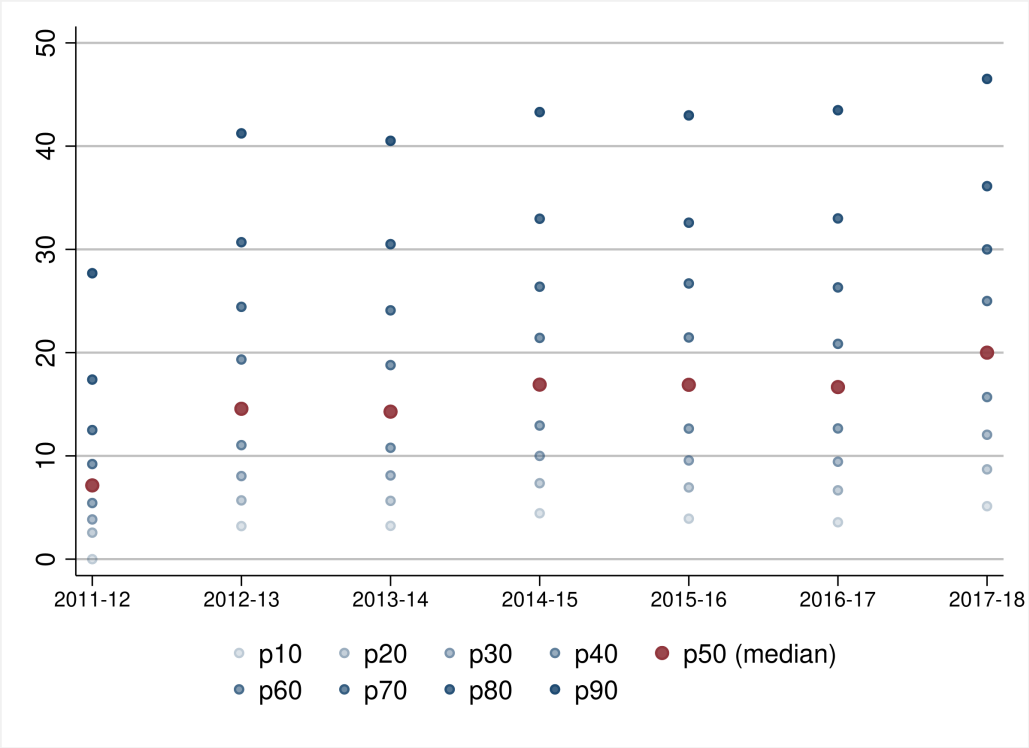

Table B1: Descriptive statistics of control variables.

	Mean	SD	Min. value	Max. value	Num. of obs.
Students' characteristics					
Female	0.51	0.50	0	1	2,266,991
On-time	0.84	0.37	0	1	2,238,975
Early attendant	0.01	0.11	0	1	2,238,975
Retained student	0.15	0.36	0	1	2,238,975
Attendance of nursery schools	0.96	0.20	0	1	2,172,506
Italian native speaker	0.93	0.33	0	2	2,148,602
Average grade prev. term	6.15	1.07	1	10	2,168,899
Grade perc. rank in the class	0.48	0.29	0	1	2,168,899
Average grade prev. term	6.15	1.07	1	10	2,168,899
Grade perc. rank in the class	0.48	0.29	0	1	2,168,899
Hh socio-economic level - q1	0.26	0.44	0	1	2,145,892
Hh socio-economic level - q2	0.25	0.43	0	1	2,145,892
Hh socio-economic level - q3	0.25	0.43	0	1	2,145,892
Hh socio-economic level - q4	0.24	0.43	0	1	2,145,892
Classes' characteristics					
Sh Female	0.51	0.29	0	1	2,364,963
Sh Early entrants	0.01	0.04	0	1	2,356,845
Sh Retained	0.15	0.16	0	1	2,356,845
Sh Foreign EU students	0.05	0.08	0	1	2,353,321
Sh extra-EU students	0.05	0.07	0	1	2,353,321
Class size	19.19	4.71	8	37	2,376,576
Sh Italian-born father	0.89	0.12	0	1	2,342,931
Sh Italian-born mother	0.87	0.12	0	1	2,342,973
Schools' characteristics					
Sh Female	0.51	0.21	0	1	2,376,151
Sh Early entrants	0.01	0.03	0	0.67	2,371,590
Sh Retained	0.15	0.12	0	1	2,371,590
Sh Foreign EU students	0.05	0.05	0	0.83	2,372,466
Sh extra-EU students	0.05	0.04	0	0.51	2,372,466
School size	166.57	72.88	11	557	2,376,576
Sh Italian-born father	0.89	0.08	0	1	2,372,347
Sh Italian-born mother	0.87	0.08	0	1	2,372,347

The table reports means, standard deviations, minima, maxima, and the number of non-missing observations for each variable. Retained, Early entrants, and On-time describe students' schooling progression in high school. Class-, and school-level variables expressed as shares are computed as the share of students in the relevant class/school with the specified characteristic.

Table B2: Balancing test (% of graduated peers' parents)

	(1)	(2)	(3)	(4)
Trends:	No trend	Linear	Quadratic	Cubic
Share of female students	-0.0424***	-0.0423***	-0.0437***	-0.0451***
	(0.0055)	(0.0064)	(0.0064)	(0.0064)
R2	0.92	0.94	0.94	0.94
N.Obs.	2007606	2007606	2007606	2007606
Share of early entrants	0.0795***	0.1313***	0.1399***	0.1485***
	(0.0222)	(0.0275)	(0.0275)	(0.0278)
R2	0.92	0.94	0.94	0.94
N.Obs.	2004904	2004904	2004904	2004904
Share of retained	-0.0142*	-0.0327***	-0.0334***	-0.0328***
	(0.0068)	(0.0079)	(0.0079)	(0.0078)
R2	0.92	0.94	0.94	0.94
N.Obs.	2004904	2004904	2004904	2004904
Share of foreign - EU	-0.0124	-0.0131	-0.0101	-0.0060
	(0.0131)	(0.0147)	(0.0146)	(0.0146)
R2	0.92	0.94	0.94	0.94
N.Obs.	2006122	2006122	2006122	2006122
Share of foreign - Extra EU	-0.0199	0.0066	0.0076	0.0053
	(0.0130)	(0.0157)	(0.0158)	(0.0158)
R2	0.92	0.94	0.94	0.94
N.Obs.	2006122	2006122	2006122	2006122
Class Size	0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
R2	0.92	0.94	0.94	0.94
N.Obs.	2007456	2007456	2007456	2007456
Share of parents born in Italy	0.0252*	0.0137	0.0125	0.0120
	(0.0101)	(0.0115)	(0.0115)	(0.0115)
R2	0.92	0.94	0.94	0.94
N.Obs.	2007573	2007573	2007573	2007573

Standard errors in parentheses. $+$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$. All regressions include school and cohort fixed effects