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ABSTRACT

In this paper we analyze whether the gender composition of classmates in high school affects the choice of college-major by shifting it towards those majors preferred by the prevalent gender in the class. We use a novel dataset of 30,000 Italian students graduated from high school between 1985 and 2005 and followed through college and in the labor market. We exploit the fact that the gender composition of the graduating high school class, from one year to the next, within School-Teacher assignment group, shows large variation that we document to be as good as random. We find that male students who attended a high school class with at least 90% of male classmates were significantly more likely to choose "prevalently male" college majors (i.e. Economics, Business and Engineering). However, in the long-run, the higher propensity to enroll in "prevalently male" majors (that are more academically demanding) did not translate in higher probability of graduating in them. In fact, male students from high school classes with >90% males ended up with lower probability of graduating altogether, and they exhibited worse university performance. The peer-pressure towards prevalently male majors may generate mismatches that are counterproductive for college performance and graduation probability of male students. We do not observe these effects on female.

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1 Introduction

Two important and well established regularities motivate this paper. First, while women have surpassed men in their college graduation rates in almost all developed countries (Goldin 2006; Turner and Bowen 1999), their choice of college major has been persistently different from that of men. Men represent a very large share of enrollment in Engineering and Business/Economics majors, which we will call Prevalently Male (PM) Majors and which tend to be relatively math-intensive, academically demanding and prestigious in most countries. Instead, they represent a minority in the Humanities and Education majors, which we will call Prevalently Female (PF) Majors[1]. As graduating in PM majors usually leads to higher paid occupations, relative to graduating in PF ones[2], these differences are responsible, in a purely accounting sense, for a significant part of the existing gender wage gap in many countries (Altonji et al. 2012). However, as college majors are chosen based on preferences and comparative skill advantages, it is far from clear that exogenously shifting people into PM majors can improve their labor market performances. Second, an extensive literature has shown that the peer environment in school can have an important effect on the academic performance and choices of students (Carrell et al. 2009 , Carrell and Hoekstra 2010). The gender composition of peers, in school and at work, has also been shown to matter, and to matter differentially for men and women, in their productive performance, and for competitive outcomes and choices[3]. Several studies show that men and women are affected differently by a working environment made mainly of same-sex peers. In particular, men tend to be more confident (sometimes overconfident) in competitive situations while women under-perform and show lower confidence under competition pressure (Bengtsson et al. 2005, Niederle and Vesterlund 2011).

Our research analyzes whether there is a causal effect of the gender composition of the peers in high school on the choice of college major. We also analyze whether such an effect differs between men and women. In particular we focus on whether a large presence of same-gender classmates increases the probability of choosing a college major typically associated with that gender. We also analyze whether this effect on the initial choice of major has long-run consequences or if it is "undone" in the following years. Finally we analyze whether it affects the performance in college and the earnings on the labor market. Let us emphasize that we simply aim at establishing causation from peer gender to the individual choice of major. While we will speculate on, and discuss potential channels and mechanisms, we are unable to state whether the effect is due to imitation of peers' choice, pressure or to other features of the interaction among peers of the same gender.

We consider a specific group of peers, the high school classmates, that in our case constitutes a very important

[1] The U.S. Digest of Educational Statistics (2011) shows that only 18% of recent graduates in Engineering, but 64% of graduates in the Humanities, were women (U.S. Digest of Educational Statistics (2011).

[2] According to the U.S. Digest of Educational Statistics (2011) the average salary of a full-time employee one year after graduation was $ 54,900 if she had a bachelor degree in Engineering but only $ 31,500 if she had a bachelor degree in the Humanities (U.S. Digest of Education Statistics 2011 website - table 404).

[3] For instance Gneezy, Niederle and Rustichini (2003) Niederle and Vesterlund (2007) show different degree of competitive behavior of men and women in same-gender environments, through an experimental setting. Booth and Nolen. (2012) and Booth et al. (2013) show difference in performance of men and women in class with different gender composition.

social group for the individuals analyzed at the time of choice of college major. We ask the following question: do men who attended high school classes with a very large share of males show higher likelihood to choose PM college majors? Conversely, are women who attended classes with a very large share of female classmate, more likely to choose more PF college majors? and how are their University and labor market performances affected by such a choice?

There are two main challenges in setting up an appropriate research design to answer these questions. First, we need to observe the gender composition of peers of an individual at the time she/he develops the choice of college major, and then follow her/him in her/his college career and into the labor market. Second, to draw causal inference, we need an environment in which the gender ratio of high school classmates (peers) is as good as random. In particular it should not be correlated to other characteristics of the individual, of her/his family background, of the teachers and of the class attended.

To address both these challenges we rely on a new dataset that we collected and organized merging school and administrative records. It contains longitudinal information on family background, high school class and peers, school performance, college career and wages for about 30,000 students, who graduated from college preparatory high schools in Milano, Italy, between 1985 and 2005. Three reasons make these data uniquely fit to study the effect of peer gender composition on the choice of college major and its consequences. First, in Italian high schools students are assigned to a class (usually made of 20 to 25 peers, but sometimes as small as 15 peers) when they first enroll. Except for small rates of attrition, they share with peers in this class the same set of teachers and the same academic curriculum for 5 years (from 13 to 18 years old). The classmates that we observe in the last year of high school, therefore, interacted with each other for most of the previous five years of their school life, a period in which their personal identities were shaped and college choices were developed. Second, individuals had no control on the gender composition of their class. Students were assigned to "sections" (in Italian "sezioni") identified with a letter (A, B, C...) by the principal of the school in their first year of their high school career. They remained in that "section" sharing the same set of teachers and classmates from grade 1 to grade 5 and we can identify a student's "section" and class in our data[4]. Year after year each "section" was assigned a new group of students (class) in its first grade (say 1-A) who graduated 5 years later (as 5-A). The gender ratio of classes graduating in different years from the same section varied significantly, in a way that appears to be completely random (as we will show) and totally uncorrelated with other class characteristics. There was no prescription to balance the gender ratio in a class, and therefore some random accidents (e.g. different gender ratio in cohorts, different size of cohorts, different size of classes and random assignment) produced random variation of gender ratio across graduating classes within section. This

[4]A Section in a school in a specific year is a bundle of 5 classes (one per grade), named with the same letter, say 1-A, 2-A, 3-A, 4-A, 5-A. Each year one new class enters the section (1-A) and one graduates (5-A). Classes in a section share the same set of teachers year after year.

is an ideal context to separate effects of the class gender-ratio from those due to school, cohort and teachers. Finally, thanks to a significant data collection effort[5] that we describe below, the extent and detail of our data on the 30,000 individuals is remarkable. Those data include information on high school, cohort, class, identity of their peers, year of graduation, residence address when in high school and exit-test scores. Moreover we have merged this information with that on college career (choice of major, graduation date, university attended) on labor market outcomes (earnings in year 2005, occupational choice) and on their family background.

The main outcomes that we analyze are the choice of college major and the subsequent performance in college. In Italy such a choice is made at the end of high school. It is costly to change later, as one would have to re-enroll and start the new major from the beginning. Hence, major of enrollment is highly correlated with major of graduation. It is also correlated with labor market outcomes. In our work we organized majors into 11 groups. To sharpen our analysis we further group those 11 majors into three categories associated with significantly different share of females (males) among enrolled students . Figure 1 shows the female share among total enrolled students for the 11 college majors from our sample (measured in the right scale and reported as the darker grey histogram). We rank majors from left to right according to this share and we define the two majors with smallest share of women (Engineering and Economics/Business) as Prevalently Male (PM) Majors. They are the only two majors in which females constitute less than 40% of enrolled students. At the opposite end of the spectrum Humanities and Education are the two majors showing the largest share of women among enrolled students and we call them Prevalently Female (PF) Majors. Those two majors are the only two with more than 70% of women among enrolled students.

The prevalence of males and females in those majors is a feature of most developed countries (see Flabbi 2012). All the other majors, who have a less extreme gender distribution between male and female enrolled are defined as Gender Balanced (GB) majors[6]. Figure 1 also shows, as light grey bars, the average yearly wage in year 2005 by major of graduation (left scale), as measured in our sample (not corrected for any characteristics). Interestingly we notice that the PM majors are also associated with the highest earnings while the PF majors are associated with lowest earnings. This suggests that the different choice of major across gender may account mechanically for a significant part of the earning gap between men and women. However, as skills and preference determine the choice of major and they differ between men and women, the correlation shown above does not reveal what would be the effect of changing major choice on earnings for two identical individuals, males of females.

The most relevant findings of our empirical analysis are three. First, we find that male students attending a high school class with more than 90% of male classmates have a probability to choose a Prevalently Male (PM)

[5]We are grateful to the Fondazione Rodolfo Debenedetti and to Universita' Bocconi for contributing to the funding of the data collection.

[6]In robustness checks (available upon request) we alternatively considered the top and bottom three majors in terms of share of female, denoting them as PM and PF majors. The main findings presented in the paper remain very similar.

Major that is 10 percentage points higher relative to the average probability (41 percentage points). Women, on the other hand, do not seem to be affected in their choice of major by very large share of women (or men) in their high school class. Second, the increase in probability of choosing PM Majors for males who attended high school classes with more than 90% males, seems particularly strong for those in the lower part of the academic quality distribution (as measured from high school test scores). That group increased the frequency of PM choice by 39 percentage points, from a baseline of 25 percent chances of choosing such majors. Third as PM majors are more math-intensive and academically demanding, the higher probability of choosing them caused lower academic performance of those males as measured by graduation rates, time to graduation and final college score. Males graduating from classes that are >90% males have lower university performance and lower probability of graduating than other identical males. There are no significant effects on their labor market earnings.

A possible interpretation of the result is that the pressure of male peers affect male individuals' choice, generating overconfidence and mismatches in PM majors. These decisions result in lower graduation rates in the long-run with a potentially detrimental effect on university career. This result shows the importance of evaluating peer effects in the long-run. Some of those short-run effects could indeed be reversed in the long run when the peer influence vanishes. Women, instead, perhaps because they tend to shy away from competitive majors (Niederle and Vesterlund, 2011) do not seem to be subject to these type of peer effects. Further research is needed to understand if these differences between men and women are systematic and apply to other choices and environments.

The rest of the paper is organized as follows. In section 2 we frame our paper within the literature. In section 3 we present our dataset and we illustrate more carefully the correlation of PM/PF Major choice with earnings and with earning gender gap. In section 4 we present our identification strategy and we establish the randomness in the class gender ratio of our sample. In section 5 we show results on the effects of high school class gender composition on the choice of major and on college and labor market outcomes. In section 6 we explore some checks and extensions and we suggest some possible channels for the identified effects. We conclude our analysis discussing implications of our findings in the final section 7.

2 Literature Review

The literature on the effect of peer gender-composition on individual choices and outcomes is not very large but it is growing fast. Most of the older literature analyzed differences between students in same-sex versus coed schools leaving unsolved the issue of selection (versus causation). Solnick (1995) considers data on the anticipated and the final college majors of 1700 female students at eight single-sex colleges and compares those with the choice of 818 female students at seven coed colleges. She tests whether women at single-sex colleges are more likely than their counterparts in coed institutions to stay in traditionally male-dominated fields. The possibility of women to sort themselves across schools, however, and the differences between schools generate serious possibility of school and individual level omitted variables correlated with outcomes.

Billger (2002) exploits the case of a female college becoming coed to estimate the effects of attending a women's college on the choice of college major, the probability of degree attainment, and the occupational choice. The study compares women in the all-female cohorts with those in the coed cohorts to see whether women pursued different fields and careers. After the admission of men, female students were significantly less likely to pursue male dominated college majors and occupations. The interpretation of these results is that coeducational settings might reinforce gender stereotypes, while single-sex schooling might give more freedom to explore interests and abilities beyond socially constructed roles, especially for female students. A more recent paper by the same author however, Billger (2009), questions this earlier evidence by using more refined econometrics techniques. In this work Billger exploits the fact that "Title IX" allowed for the first time the creation of single-sex public schooling in the US to investigate whether single-sex schooling leads to improved labor market outcomes. Results show that single-sex education graduates are no more likely to pursue college degrees, and are less likely to meet their own educational expectations then graduates from coed educational environments. Of related interest is a recent working paper by Favara (2012) that looks in detail to educational choices in single-sex schools. She finds that attending a single-sex school leads students to a less stereotyped educational choice.

The contributions described above, however, have not been able to deal convincingly with the selection issue. The choice of one-sex or coed education is not random and can be correlated with academic, personal and family attributes of women (and men). Moreover coed and non-coed schools may differ on other dimensions such as teacher quality, resources, and those are not always observed by the researcher. Better labor market outcomes, or specific major choices, might be the result of career-focused women selecting single-sex institutions or they may derive from same-sex schools being different under other respects. More recently, to address these issues, scholars have used random selection into different schools and classes to identify more credible causal effects. Park et al (2012) use the case of South Korea, where assignment to all-girls, all-boys or coeducational high schools is random. They use administrative data on national college entrance, mathematics examination scores for a longitudinal survey of high school seniors and find significantly positive effects of all-boys schools in enhancing outcomes in college related to the performance in Science, Math and Engineering. They do not find comparable effect for girls. In a related study Park et al (2013) also find that single-sex schools produce a higher percentage of graduates who attended four-year colleges and a lower percentage of graduates who attended two-year college. While these studies circumvent the problem of selection into a school, they still are unable to separate the "peer-gender" effect from effects stemming from other unobservable school characteristics (gender and quality of teachers, spending per student in the school and so on). Partially addressing these issues a recent paper by Booth et al (2014) sets up an experiment to assign students to all-female, all-male, and coed sections in the same university major. This method solves the selection issues and it also keep fixed the unobservable characteristic of the college and of teachers. They find that one hour a week of single-sex education benefits females making them 7% more likely to pass their first year courses and score 10% higher in their required second year classes than their peers attending coeducational classes. Their experiment, however, is limited to very short-run outcomes, passing one university class and it has a limited number of students.

Most closely related to our work is a paper by Schneeweis and Zweimuller (2012) analyzing the causal impact of the gender composition in coeducational schools on the choice of school type for female students attending primary schools in two Austrian cities. Using natural variation in the gender composition of adjacent cohorts within schools, they show that girls are less likely to choose a traditionally female dominated school type and more likely to choose a male dominated school type if they were exposed to a higher share of girls in previous grades. The results, however, are rather weak and sensitive to specifications. The sample size is rather small and authors do not have data on long-run outcomes and are unable to control for school-cohort and teacher effects. Moreover, the range of variation of the gender ratio across cohorts is quite small, so they cannot observe the outcome of an environment that is exclusively (or almost exclusively) one-gender.

Relative to the papers reviewed above our analysis has three crucial advantages. First, we allow for a much larger set of controls of the student background and student academic quality. Second, our variation is based on random changes in gender composition across classes, within section-school (which implies identical teacher composition). In such a setting we can thus keep unobservable teacher, school and cohort characteristics constant. Third, we observe long-run outcomes, besides choice of major, such as college performance, graduation rates, time to graduation and earnings once on the labor market. This turns out to be crucial to determine whether peer gender composition has effects only in the short-run or if it affects the whole academic and labor market career of individuals.

Finally, related to our paper in a general sense, is also the literature analyzing the interactions between gender and educational choice (e.g. Xie and Shauman, 2003 about women in STEM fields) and the literature on the effect of the gender of teacher on school choices and student performance (e.g. Carrell, Page and West 2010, Dee 2007). A growing experimental and theoretical literature has also analyzed differences between men and women behavior as consequence of the peer gender composition. Gneezy, Niederle and Rustichini (2003) and Niederle and Vesterlund (2007, 2010) show in experimental evidence that the gender composition of the opponents affect significantly the performance in tournaments, especially of women. Women perform significantly better in tournaments against other women than against men, while men perform better against other men.

3 Data Description

3.1 Construction of the data set

Our sample comprises individuals who graduated from college-preparatory high schools (Licei) between 1985 and 2005 in the city of Milan, Italy. These individuals are currently between the ages of 27 and 47. We gathered information from hard copies of administrative documents. While some missing and destroyed records prevented full coverage, we were able to cover more than 90% of all records for students who graduated in thirteen different schools in Milan between 1985 and 2005. The sample includes about 30,000 individuals distributed into 1371 high school classes in the last (fifth) year of high school. The high schools are equally split (respectively 6 and 7) between "Classical" and "Scientific" high schools. Both types of high schools grant access to any college major, but the first type has a curriculum more intensive in Humanities and Literature while the second type is more focused on Science and Math. Milan is a large service-oriented metropolitan area. The college educated individuals from Milano usually become professionals in business, finance, administration, education and academia. Our analysis, therefore, pertains to a group at the top of the income and educational distribution in Italy.

For these individuals we have information on the year of graduation, the score in the high school exit exam, the school attended, the location where they lived during high school and the identity of their parents. Most importantly, we know the identity of their class-mates in the last year of high school and the set of professors they shared, from the "class" and the "section" identifier.

We have then linked this dataset (using names and dates of birth) with the student records from all Universities in Milan (two private universities, Universita' Cattolica and Bocconi, and three public universities, Politecnico, University of Milano, University of Milano-Bicocca). Milano is the city that offers the best and more diverse University options in Italy, including all possible Majors. It is overwhelmingly common for high school graduates in Italy to attend University, if one exists, in the same city where they went to high school. For students graduating from a college preparatory school in Milano, enrolling in one of the local University, is by far the best choice if they intend to attend college in Italy. The information about their university career includes whether they graduated, the year, field and university of graduation and their overall exit score in University.

In a further step we linked these records with the personal income figures of the individuals in year 2005, as revealed to the internal revenue service. This is the reported total income on which individuals pay taxes. The advantage of using these data is that the administrative file of reported income includes all individuals in the national territory as it is mandatory to report any income. Hence, if a person does not appear is because he/she has no income or he/she is not on the national territory[7]. Self-employed are included in the sample. The disadvantage of the data is that we do not have a measure of labor supply (hours or weeks worked). Hence we will focus on yearly earning. Finally, we linked the address where students used to live at the time of high school to the average house value of their specific neighborhood[8]. We will use this measure as a proxy of family wealth as the house is the most important financial asset of families in Italy.

Longitudinally linked data on income, university career, high school performance and family background are rare in any country. For Italy, our originally collected database is the only one we know containing such information on such a large sample. Hence, this data provides an interesting tool to analyze long-run effect of schooling on income. We use the income data only for people who graduated from high school before 2000. Considering an average college attendance of four to five years, people in our sample would have been on the labor market between 0 and 15 years as of 2005. Hence this provides a good assessment of the long-run consequences of one's high school experience on the labor market outcomes during the working career (up to 20 years after high school graduation). Of the 30,000 individuals for which we have information about high school, 14,000 graduated between 1985 and 2000, and can be matched to the information on income in year 2005. For a stratified 10% random sub-sample of the initial sample (equal to around 3,000 individuals) we also collected more detailed information from telephone interviews conducted in June 2011 by the professional company "Carlo Erminero & Co.". The additional information covers several variables regarding family background, parental income, and extra-curricular activities while in high school. We will use some of this additional data in robustness checks.

3.2 High School Classes

In our data we can identify individuals belonging to the same graduating class in each section of each high school included in the sample. Students in Italian public schools have only limited ability of choice of the high school attended. Those determined to pursue a college education, choose one of the two types of high school, either the "Classical" one (Liceo Classico) or the "Scientific" one ("Liceo Scientifico") and usually decide to attend the school closest to their residence within the type chosen. During the period under analysis, classes were formed in the first year of high school, by pooling all enrolled students and drawing a certain number in each class. Enrollment into schools reflected the number of applicants and no selection nor cap was in place. The entry cohort varied from year to year mirroring, in part, the demographics of the relevant age group living in proximity of the school. The students we observe have shared the same classmates and professors for at least the last year of high school and, likely, for most of the five years of high school. The daily interactions at the

[7] There is also a small category of employees with only standard salary income and no deductions that need not report it. Usually this is a very small percentage of the population.

[8] We have transformed each address into geographic coordinates using Google geo-coding system and then matched each address to market value per square meter as provided by the government agency "Agenzia del territorio" for 55 different homogenous areas in Milan.

time of College choice may affect the preferences and the information available to students. Among students attending the "classical" high school track the average share of women was 67%, while they were only 40% in the scientific ones. This implies that the average gender composition of classes was more female-dominated in the classical high schools, and classes in those schools were more likely to have large shares of women. Classes with very large share of men, instead, were likely in the "scientific" high schools. Within each track, however, and within each school and "section", as we document below, the distribution of gender ratio in the classes appear to be totally random. We only use within school-section variation of class gender composition over time in our identification.

In Table 1 we present descriptive statistics for our data. We divide variables between individual-level (top portion of the Table) and class-level (bottom portion). For individual-level variables we present statistics relative to the whole sample as well as the separate means for men and women (in columns 6 and 7). We also show the t-statistic of the difference in averages (men-women). The table summarizes the information about individuals' academic career in high school and in college. The most important pre-treatment socio-economic characteristic available to us (besides age, gender, and school) is the value of the house where the students lived during their last year of high school. As house was the primary asset of families and the value of real estate varies significantly within the city of Milano, this is a good proxy for family's income.

In the sample 52.3% of individuals are female and thus 52.3% is also the average female-percentage in a class faced by the average individuals. However as we noted above there is a systematic difference in gender ratio between the scientific and the classical high schools. We have re-scaled the high school exit test score to be between 0 and 1, with 0 being the minimum passing score (60 out of 100 in the post-2000 "Maturita' " test score) and 1 the maximum score achievable (100 out of 100). Summary statistics show that the distribution of scores is skewed to the left (mean score is 0.416). Also the women's score distribution has substantially higher mean than the one of men (the t-statistics of the difference in means is 11.4). Even when we rank students according to exit-scores within school and cohort, females perform better, being ranked on average at 0.516 (on a 0 to 1 rank) versus an average rank of 0.471 for men with a t-statistic for the difference of 12.4.

Of these 29,370 high school graduates, 23,118 students (79%) enrolled in one of the Universities in Milan. Of those 23,118, 27.5% enrolled in PM Majors (Engineering, Economics & Business) with a substantial gender difference: only 13.9% of women chose one of the PM majors while 42.3% of men did. The t-statistic for the difference in means is 50.3. Of the 23,118 students enrolling in a university, 17,140 actually graduated (by 2011, when we collected the data) implying a 26% attrition rate. Out of all students enrolling in a university, 11.8% of women earned a degree in a PM major, while 32% of men did. Interestingly, conditional on enrolling in a PM Major, women had lower drop out rate than men: 17.5% versus 25% with a t-statistic of the difference equal to 6.

To complete the list of college outcomes in our dataset, women took on average 3 months less than men (t-statistic is 7) to graduate from college when the average time to completion was 6 years and 8 months [9]. At the end of college, every Italian student receives a final test-score out of 110 points, computed on the basis of G.P.A. and a final thesis[10]. We have re-scaled this final score to be between 0 and 1 (with 0 being the minimum passing score) and also for this outcome women perform better than men (0.86 versus 0.78 with a t-statistic of 30.25).

The averages for men and women, suggest substantial differences in academic performance and academic choice. The log of house value (on average 8) does not show any statistically significant difference between men and women for this wealth proxy of the family of origin. This shows that the average family background of female and male students included in our sample was roughly the same.

For what concerns labor market outcomes we observe the income for 17,004 students graduating from high school before 2001: since we have only 2005 income data available, we exclude individuals that are still attending college by 2005 since their earnings might not be representative of their potential earnings (i.e. part-time job while in college). The average log wage is 9.68 and the statistically significant difference (t-statistics is 22) across gender is 0.45 log points in favor of men. From the randomly stratified selected 10% sub-sample that was interviewed we also know that women had 30.8% probability to reach a top occupation (defined as manager, professional or director) versus 43.2% of men with a t-statistic of 7.1.

As for class-level data we observe a total of 1371 graduating classes with an average size of 21.4 students and a standard deviation of 3.8. The average share of female per class is 0.52 with a large standard deviation of 0.18. Such large standard deviation is the result of combining the "Classical High Schools" which have a significantly larger average of women, with the "Scientific High Schools" which have a larger share of men. When we separate the two types of school we see that the first group has an average share of women in a class equal to 0.66 with a standard deviation of 0.11, while the second has average equal to 0.40 also with a standard deviation of 0.12. Figure 2 shows the distribution of share of female across classes in "Scientifico" (top chart) and "Classico" (bottom chart) high schools from our sample, compared with a simulated normal distribution (dashed line) with same average and standard deviation[11]. As one can see, there is very little departure from normality. If anything there are a few more than expected classes with share of female near the average composition (around 0.4 share of females at the "Scientifico" and 0.6 at the "Classico"). In the tails of the distribution (which will determine the variation identifying our results) there seem to be no systematic deviation from normality. Overall classes range from female-only to male-only ones with a within-high school type variation that appears to be normally distributed. All of the classes with more than 90% males are in the

[9] Italian students especially during this period (1985-2005) had typically very long spells between college enrollment and graduation.

[10] The exception are engineering students who get a score out of 100. We re-scaled their scores accordingly.

[11] In matching the average and standard deviation of the simulated and observed normal distribution of female shares we accounted for the fact that the observed share distribution has to be between 0 and 1 and hence it is a censored normal.

scientific high schools and all but one of those with more than 90% female are in the classical high schools.

The average students' exit score by class ranges from 0.12 to 0.78, showing high variance in the ability composition of classes. Finally the average socioeconomic status of classes captured by the percentage of students in the class that live in houses at the bottom 10% of the house value distribution has also large variation. There are, for instance, classes composed by only students coming from families in the bottom decile of the wealth distribution (they were in schools located in poor neighborhoods). The highest percentage of students in a class living in houses at the top 10% of the value distribution was 57%.

3.3 Prevalently Male and Prevalently Female Majors and Earnings

As suggested by Figure 1, there is a significant difference in the average earnings of graduates from different college majors in our sample. To make this correlation somewhat more formal, and to quantify it, in Table 2 we regress the logarithm of earnings in 2005 on a series of individual characteristics and on the Prevalently Male (PM) and Prevalently Female (PF) dummies (leaving Gender Balanced majors as the omitted category), defined as graduating from the corresponding majors. The controls include the standardized high school exit score, the final college exit score, a dummy for living in a house in the top 10% of price distribution at the time of high school, one for living in a house in the bottom 10% and school-by-cohort fixed effects to control for cohort-specific and high-school specific factors. The regressions, shown separately for men and women (Columns 1 and 2 of Table 2) reveal substantial positive earning gaps, associated to graduating from PM majors and significant negative earning gaps associated with graduating from PF majors. Women with similar observable characteristics, earn 0.65 logarithmic point more (92% more) if they graduated from a PM major relative to those graduating from a GB one (the omitted category). On the other hand they earn 23% less if they graduated from PF majors (relative to GB). The estimate for males is equal to a 73% earning premium (0.55 log points) from PM relative to GB and to a 42% penalty for PF graduates. The regression reveals also that the college exit score has a strong correlation with earnings, while the family house value is much less correlated with them. Keeping in mind that the family of origin of these students were in the middle and upper middle class, this implies that, conditional on that, abilities and education, more than family wealth, predicts their earnings. Clearly no causal interpretation can be attached to these coefficients; they are simply a measure of the partial correlation between major and earnings.

Columns (3) and (4) of Table 2 show another interesting fact. They identify the role played by college majors in accounting for the earning gap between men and women. In column (3) men and women are pooled and the coefficient on the female dummy is an estimate of the average gap (in logarithmic points) in income between women and men (controlling for all the individual and family characteristics described above). Remarkably, this difference equals -0.4 logarithmic points (about 33% [12] in favor of men), which is a very large average difference[13].

In columns (4) we simply add to the previous controls a dummy for PM and one for PF majors. Besides being very significant, as expected, the introduction of these two dummies, by accounting for the major of graduation, reduces the men-women earning gap from 0.4 to 0.25 logarithmic points (from 33% to 22%). Hence, one third of the men-women earning gap is accounted for by their lower graduation rates from PM Majors and higher graduation rates from PF Majors. As individuals choose the college major based on their abilities and preferences, however, the correlation shown above are far from establishing causality. Although one may be tempted, we should not infer that by shifting (randomly) people into PM majors they would increase their wage by the estimated amount. What we will analyze in our paper is whether a shift in PM major enrollment, driven by randomly distributed peer characteristics, has any lasting effect on the university and labor career of individuals.

4 Identification Strategy

The vast majority of Italian students, from rich and poor families, attend public (rather than private) high schools. In Milano the good reputation of the 13 schools that we selected (and the fact that they encompass all but one public "Liceo Classico and Scientifico" in the municipality) imply that most youth, who intended to go to college, attended one of them. As they were all public schools, there was virtually no difference in the monetary cost of attending [14].

Within each high school, as described in the introduction, students were assigned by principals to one "section", coded with a letter: A, B, C..., at the beginning of the five year cycle and stayed in this letter-section for five years (except for small attrition and transfer rates) sharing the same group of classmates and teachers. We cannot verify directly whether the principals formally followed a random assignment practise of students in one cohort across sections. Anecdotal evidence suggests that assignment to "sections" might have been affected by families exercising some pressure on the schools to have their children assigned to specific group of teachers. This mechanism could potentially introduce correlation between individual characteristics (as wealth, ability) in a section and quality of teachers . This would be an issue if this mechanism were also correlated to the gender ratio in the class and if we used variation of gender-ratio across sections. Instead, we use only within school-section variation of gender composition across classes graduating in different years (i.e. across cohorts,

[12] The conversion from logarithmic points into percentage is always calculated as the exponential of the logarithmic points minus one.

[13] This measure of earning gap is not far from what estimated for Italy in the recent years. The gender gap in yearly wages estimated from the EU-SILC data (a representative household sample), and limited to college educated over 25 was 34% in 2009, while for all workers it was 40%.

[14] All public schools charge minimal fee per year. Currently it is $150 per year. It was far less during the years 1985-2005.

within section). A unique set of teachers was assigned to each specific "section", codified by a letter, and stayed with it, year after year, for the whole tenure at the school. Sharing the same section-letter thus meant that classes graduating in that section year after year shared the same set of teachers. Hence we control for school/section. Even more conservatively, in several specifications, as the set of professors in a "section" changed slowly due to natural turnover and attrition, we include "school-section-by-five-year" dummies to be sure that each fixed effect captures the same set of professors (attrition within 5 years was negligible). We also control for the characteristics of the cohort graduating from a school by introducing school/cohort effects. This type of identification is reminiscent of the method used in other education contexts where there was no certainty of random assignment (see Hoxby 2000, Carrell and Hoekstra 2010 and Lavy and Schlosser 2011).

To make sure that the variation of the gender composition within "section" across classes graduating in different years is "as good as random" and orthogonal to other observable pre-existing characteristics of the students we perform a series of checks. First, as already shown in Figure 2, the distribution of female share across classes within each type of school appears to be close to a normal random distribution. Second, in Table 3 we show the correlation of different measures of the gender composition of a class with the observable pre-determined characteristics of students in the class. The units of observations are classes and the dependent variables are described at the top of the Table, for each specification. Specification (1) uses the share of women in the class as dependent variable, specification (2) and (3) use a dummy for being an all-female or an all male class (respectively), column (4) and (5) use a dummy for a share larger than 90% for females and males in the class, respectively, and specification(6) and (7) use a dummy for a share larger than 75% for females and males in the class, respectively. We check the correlations of these measures of gender-composition with the share of students from the wealthiest families (living in homes with value per square meter in the top 10% of Milan house value distribution) and the share of students coming from the less affluent families (living in homes with value per square meter in the bottom 10% of the distribution). We also include the mean of the logarithm of house value in the block where the student lived. We include measures of the size of the class (whether it was in the top 25% or in the bottom 25% of the size distribution) and measures of the average distance of students from school as well as an Herfindhal index of concentration of students in the class in city-blocks. These measures check whether classes with a certain gender composition are also made of students living close to each other, which could suggest the clustering of pre-existing friends in the same class. We control for school-cohort fixed effects and for "School-section-5 years" effects. None of those variables, that proxy for family location, wealth, class size and pre-existing ties between students have significant correlation with any of the gender composition measures.

In Figure 3 we plot, for each school-section and graduation cohort t in our sample, the female share for the class that graduated in year t versus the female share for the class in the same school-section that graduated in year $t-1$. The graph shows the scatterplot dividing between classical (bottom chart) and scientific (top chart) high schools. It is evident even from a cursory look that the share of female in a class has no correlation with the share of women in the same section-class graduating the following year. Moreover it is clear by the range of variation of the scatterplot, that several section-school experience a prevalently male class graduating in a year followed by a prevalently female class graduating the previous year. Table 4 tests this in a regression setting, by regressing the share of female in the school-section-class graduating in year t on the share of females in the same school-section in the class graduating in year $t-1$. In column 1 we control for school fixed effects. In column 2 we control for school/cohort fixed effects and in column 3 we add also the dummy for "School-section". The results show that the autocorrelation of female shares between class t and class $t-1$ is indistinguishable from zero.

What are the random sources of variation of gender-composition within Sections across graduation years? As we mentioned there are several accidents that produce such variation. The composition of the entry cohort, the attrition over years or pure randomness interacted with the small size of classes. One of the determinants should certainly be the overall share of females in the cohort attending the school in a year. That share fluctuates over time because of demographic random shocks in the population living near the school, and it is in no form under the control of the high school. Table 5 shows the effect of including the female share in the cohort that entered the school as explanatory variable for the female share in a specific section-class in that cohort (while the rest of the table is structured exactly as Table 3). The effect is very significant. That share also affects positively (and significantly) the probability of having classes with 90% or more women and classes with 75% or more women. Even the more extreme event of having an all female class depends positively (although not significantly) on that share. Similarly the female share in the cohort reduces (sometimes significantly) the probability of having all male classes and classes with 90% or more males and classes with 75% or more males. Taken together these tests suggest that variations of gender composition of classes within a school-section are idiosyncratically fluctuating year after year, they are not correlated with other class characteristics and they are driven by random factors such as the gender composition of the entering cohort, amplified by small size classes.

Let us mention, in concluding this section, that we have also performed more stringent tests to verify that there is no correlation between individual characteristics and the average characteristic (not just the gender ratio) in the class, using cross-year variation within a section. Following Guryan et al. 2009 in Table A1 of the Appendix we analyze the correlation between some pre-determined individual characteristics and the average of that characteristic in the class, once we control for the average characteristic of the cohort. We consider the log value of the house, the distance from the school, the probability of being in the top 10% of value distribution of houses or in the bottom 10%. In no case we find any correlation. This reveals that student characteristics within a school-section across classes graduating in different years, vary in a purely random way.

5 Main Specification and Results

The main empirical model that we estimate in the paper, always separately for males and female, is as follows:

$$y_{i,l,s,t} = \phi_{s,t} + \phi_{l,s,T} + \beta(CGC)_{l,s,t} + \delta X_{i,l,s,t} + \gamma Z_{l,s,t} + \varepsilon_{i,l,s,t} \tag{1}$$

The outcome $y_{i,l,s,t}$ is relative to individual i, in "letter section" l, in school s, in the class graduating in year t. In our main specifications the outcome variable equals one if the individual chooses a Prevalently Male (PM) college major (or a PF major, or a GB major) and 0 otherwise. The term $\phi_{s,t}$ captures all the school by year fixed effects, accounting for most of the characteristics (funding, curriculum offered, overall size, principal) that may change across years and schools. The term $\phi_{l,s,T}$ captures School-Section-by five year effects ($T = 5$) and hence it controls for the teacher composition, which is the most important characteristic of a Section in a school. The term $CGC_{l,s,t}$ represents the main explanatory variable of our analysis and hence β is the coefficient of interest. It captures a measure of the "Gender Composition of the Class" graduating in year t from section l of school s. Most frequently in our analysis that variable will be a dummy equal to one for classes with more than 90% classmates of the same sex as student i and 0 otherwise.

The variables $X_{i,l,s,t}$ control for the characteristics of individual i that we can observe. They include the academic quality of the individual measured as rank position of individual i within school and cohort in the final high school exit test-score (as a measure of skills). And they include the measure of family house value as proxy for family wealth. Finally we control for observable class-level characteristics $Z_{l,s,t}$. They include a dummy for class size in the bottom 25% of the observed class size distribution and one for class size in top 25%, class geographical concentration measured as Herfindhal index of concentration of the students' homes across city-blocks, the share of students in the class in bottom 10% of house value and share of students in class in top 10% of house value. Besides estimating separately specification (1) for men and women, we will also consider it separately for students in different parts of the ability distribution and in different parts of the wealth distribution, to see if peer gender has different effect for the choice of some specific groups.

We will also consider other outcomes $y_{i,l,s,t}$ besides the choice of college major. Our data, differently from those of any previous study of this type, allow us to follow students in their University career and labor market. Some of the measured outcomes occur five to ten years after the end of high school. We consider several measures of performance in college (such as the graduation rate, time to graduation and the exit test score in college). Other outcomes occur decades after the end of high school, such as realization of earnings on the labor market (log of earnings). In all the estimates we cluster the standard errors at the school/cohort level[15].

The next section 5.1 shows the main results on the effect of gender composition of the class on the choice of

[15] We have also clustered at the more conservative school level. Results are essentially identical. If anything some standard errors become smaller for some women outcomes, possibly revealing some negative correlation of errors across cohorts within schools.

college major. Then in section 5.2 we look at the effect of class gender composition on academic outcomes in college. Finally in section 5.3 we look at the effect on the earnings. In all cases we separately analyze the effect for men and women.

5.1 Class Gender Composition and Choice of Major

Table 6 shows the main results for the basic specifications, using alternative measures that capture a class gender composition. Columns (1) to (4) of the Table report results for female students, while columns (5) to (8) reports the results for male students. Within gender, the columns of the table differ in the explanatory variable used to capture class gender composition, as we describe below. In panel A of the table, the outcome variable is a dummy for enrolling, after high school, in a Prevalently Male (PM) college major. In Panel B the outcome is enrolling in a Gender Balanced (GB) major, while in Panel C the outcome is enrollment in Prevalently Female (PF) college major. The full set of individual level controls, class level controls and fixed effects is included in all regressions as noted at the bottom of the table. We first check whether there is a linear relation between outcomes and the share of same gender classmates, by simply including in specification (1) for females and (5) for males the share of the classmates of the same gender. Then we analyze whether strongly unbalanced gender composition of the classes affect the major choice. As most of the literature analyzes whether same-gender set-up have different educational impact than coed ones, we consider classes which are completely (100%) or "overwhelmingly" (90%) single-gender. In specification (2) for women and (6) for men the main explanatory variable is a dummy equal to one when 100% of classmates are of the same gender. In specification (3) and (7) the main explanatory variable is a dummy equal to one when more than 90% of classmate are of the same gender (female and male respectively). Finally in specifications (4) and (8) we analyze whether classes overwhelmingly of the *opposite* gender have an impact. To do this the main explanatory variable is a dummy for classes in which the share of classmates of the same gender is less than 10%.

The estimates reveal some interesting effects that differ between men and women. First, our data show no evidence that the share of same gender peers affect in a linear way the probability of choosing PM or PF majors for either males of females. This emphasizes that in the presence of "small variations" in gender composition of classes around the average (as is the identifying variation available to some previous studies such as Schneewiss and Zweimuller 2012), one may not identify any effect on the choice of college major. The second interesting result is that the major choice of women is not significantly affected even by the more extreme gender composition of the classes. Girls in all-female (or >90% female) classes do not exhibit different propensity of enrolling in PF (or in PM) majors. Similarly girls in mostly male classes do not show any stronger propensity to enrol in PM majors. Male students, instead, show a significantly larger probability of enrolling in Prevalently Male majors if they have attended an all male or a >90% male class. The estimated size of the effect is that by attending a >90% male class, a male student increases his probability of enrolling in PM majors by 13.1 percentage points. The average probability to enrol such majors is 42.7 percentage points for males, hence the effect is large and significant. Interestingly and somewhat symmetrically, males have a smaller probability of enrolling in PM majors if they attended a class that was >90% female. However this effect (reported in column 8) is only significant at 20% confidence level. Panel B and C of Table 6 reveal that the shift into PM majors for males takes place by diverting students out of Gender Balanced Majors. Males decrease their probability of enrolling in GB majors by about 10 percentage points, which corresponds to the increase in PM majors. This suggests that some males with "marginal" preferences for GB majors are pushed into PM majors when they are choosing within a group of peers that is overwhelmingly male. In all regressions we control for individual ability/academic performance in high school (as proxied by within school-cohort rank in the high school exit score) and in Table A2 of the appendix we also control for the average class ability (proxied by their average school-cohort rank in high school exit test score). The peer-gender effect does not seem to be working through the academic quality of the class or of the individual and is present when controlling for them [16].

This result is indicative of the fact that peers, and their gender, can affect preferences and attitudes. It is consistent with the idea that males show a more confident and competitive behavior when exposed to other males (as consistent with Bengtsson et al. 2005, Niederle and Vesterlund 2011). The increase in their probability of choosing PM college majors, in fact, will expose them to a more academically challenging curriculum and environment when in college. The average academic quality in PM majors is higher than in PF (or GB) ones. High school graduates enrolling in PM majors have an average high school exit score of 0.51, those enrolling in PF majors 0.42 and 0.38 for GB majors. This may imply that males from prevalently male high school class choosing PM majors have a lower average quality than other male students going on to PM majors. They may be "pressured" into majors that are a worse match for their abilities and this can affect their performance in college. On the other hand these majors are associated with a wage premium, hence in spite of the mismatch, this peer-effect may result in higher wages on the labor market if being exposed to knowledge in those fields increases earning abilities. We will address these questions in the next sections.

Table 7 analyzes the effects of class gender composition on the choice of students, partitioned by academic ability. We focus on the measure of class gender composition that was found to be significant in Table 6, namely the >90% same sex share dummy[17]. We show again the main estimated effect of being in a class prevalently (>90%) of the same gender (in column 1 and 4) and then we separate the effects, by splitting the sample between individuals whose measure of academic performance, as revealed by their high school text score, was

[16] In a robustness check we show that high school exit score as outcome is uncorrelated with class gender. In Appendix Table A3 we omit both individual and class average within school-cohort rank in high school exit score as controls and the effect of the gender composition variable on the probability of PM major choice does not change. Both tests suggest orthogonality between class gender composition and high school test performance in our setting.

[17] Table A4 in the online appendix uses the dummy "Same gender only class" as explanatory variable and finds similar effects as those shown in Table 6, for men and women.

in the bottom quartile of the gender/school/cohort distribution (Bottom quality) and those whose performance was in the top quartile (Top quality). We show the effect of the >90% dummy on each of the two quartiles in column (2) and (3) for females and in columns (5) and (6) for males. The effects for women are mainly non significant, with only one marginally significant but not too large effect on bottom-quality women. Class gender composition is not significantly associated with different major choice for women. The positive average effect on the probability of PM major choice for men, instead, is present for both quality sub-groups, and much larger and significant for the group in the bottom academic quality. For that group of male students, being in a prevalently male class increases the probability of choosing a PM college major by almost 46.5 percentage points. For high quality students, instead, the effect is only 12 percentage points and it is not statistically significant. This is particularly remarkable because the average probability of choosing a PM major for bottom quartile male students is only 25.5 percent. Hence graduating from a prevalently male class makes that probability almost three times larger. Panels B and C reveal that three quarters of the shift to PM majors for bottom quality students is from GB majors and one quarter from PF majors. Those panels also reveal a smaller shift by 12 percentage points , from GB majors to PM majors for male students in the top quality quartile in predominantly male classes. This may reveal that students in a prevalently male class with a marginal preference for math-engineering-business and not academically strong, are subject to pressure/competition or overconfidence pushing them towards more demanding, but also more prestigious majors. On the other hand better achieving students (who were already choosing PM majors with very high probability, equal to 55% on average) seem less influenced by such class environment[18].

Table 8 separates the effects for students from families in the bottom and top quartile of the house value distribution, which could be considered as proxy for economic well-being. Similarly to what done in Table 7 we show again the total effects for males and females (in Columns 1 and 4) and for the sub-group of students in bottom and top quartiles of house value (column 2 and 3 for women and 5 and 6 for men). While the effects on women are, as usual, not significant, in this case male students from families in the bottom-part of the house value distribution were those more affected by the prevalently male peers. For this group graduating from a class that was >90% males implied 24.7 percentage points higher probability of choosing PM majors. This corresponded to an almost equally lower probability of enrolling in GB majors. To the contrary, male students from families in the top quartile of the house value did not show significantly different choice of major when graduating from a >90% male class. Possibly the group of students from higher income families had parents that were more likely to be involved and influential in their children' decision of College major. Hence they may have formed their preferences mainly based on their family environment and were less subject to peer influence.

[18]In Table A5 in the online appendix we split the male and female sample into above-below the median (rather than top-bottom quartile) of the academic quality distribution. We obtain effects of the ">90% same gender share" only for male and stronger for the low quality groups. We do not find effects for either group of women. This fully confirms the results of Table 7.

To the contrary, male students from less wealthy family may have had less parental involvement in the process of major choice which resulted in stronger peer effects. Another interesting effect, revealed by our regression for male students in families in the top quartile of house value distribution, is that they are less likely to enroll in a PF major if graduating from a >90% male high school class. Hence the dominant male composition of the class affects also this group by shifting students from PF to Gender Balanced majors but the effect does not seem as strong.

5.2 Performance in College

In the Universities of our sample, PM majors (Engineering and Economics-Business) were more math intensive, more prestigious and more academically demanding than GB or PF majors. Using as metric the high school graduation test score from an exit exam common to all schools (re-scaled to be between 0 and 1), students enrolled in the PM majors had an average of 0.51, those enrolled in PF majors 0.42 and 0.38 for GB. The differences are large and significant. Hence, if prevalently male classes pressured male students, and particularly those with low academic quality, towards enrolling in those majors, this could imply that the college performance of males graduating from a >90% male class were worse than the rest. Some marginal students may have been pushed into majors that were bad matches for their abilities with negative effects on their performance. De Giorgi, Pellizzari and Redaelli (2010) found that peer-pressure, or peer-imitation in College increased mismatch in the choice of students who chose classes and majors in which they had comparative disadvantages, with negative impact on their performance. We want to test whether such effect is present also in our data. Even more worrying, as transferring to another major is costly in Italy after enrolling and investing in one major, the lower performance and mismatched skills may translate in lower probability of completing college altogether. The effect of graduating from a >90% same gender class on different college outcomes are shown in Table 9. In Panel A the dependent variable is the probability of graduating from the major of first enrollment. In panel B the outcome is probability of graduating altogether, by 2011. In Panel C we analyze the probability of graduating in PM majors (even if not the same of initial enrollment). In panel D we analyze the effect on time to graduation (in months) for those who graduated, and in Panel E the outcome is the final graduation score in College. The regression include all the individual and class control as in Table 6 and also Major and University fixed effects, accounting for differences in curriculum and quality.

Looking first at the impact on women out of 15 coefficients only one is significant at the 5% level. As graduating from a prevalently female class did not have an impact on the choice of major it is reasonable to find that it does not affect the performance in college either. To the contrary for males, graduating from a >90% male class is associated with a 8.6 percent lower probability of graduating in the major of enrollment. The effect is about the same magnitude as the percentage increase in PM major enrollment found in Table 6.

It suggests that male peers might have pressured marginal male students into PM majors but most of them did not have the commitment and relative ability to graduate from them. Some of them may have dropped out, others may have quit and then enrolled in another major. Clearly the graduation rate effect suggests an increased mismatch for this group of male students. Even more worrying is the effect shown in Panel B. Those individuals graduating from >90% male classes had a lower probability of graduating altogether by a significant 8.1 percentage points. The mismatch might have worsened their initial performance and pushed them out of college altogether. Notice that the negative effects on students from the bottom quality quartile (Column 5) are much larger in their point estimates, but also rather imprecise and hence only the effects on top-quality students are significant (Column 6)

Panel C looks at whether the group of males from >90% male classes had a higher probability of graduating (rather than enrolling) in PM majors. In Table 6 we have seen their larger probability of enrolling PM major, and in Panel A of this table we have seen that part of that effect dissipates as those students did not graduate, but what is the net effect? The estimates show that this group is neither more nor less likely to graduate from PM. The point estimate for the whole group is negative but only significant at 10% level. Hence, dropouts and transfers undo the peer-gender effect that had pushed these males towards PM majors. Male peer potentially induced over-confidence, or imitation prevailed in the choice. In any case the consequences of the peer-effects did not last till the end of college. Finally panels D and E show that the group of males from >90% male classes took longer to graduate and had lower performance, especially those in the bottom quality quartile (they took 9 extra months to graduate and had a final score 0.13 points lower on an average of 0.69).

Combining the regression results we see that the gender composition of high school classmates is a random shock that affected the gender of peers and influenced their choice of major during the last year of high school. We found this effect to be present for males but not for females. However, such peer effect was not enough to change the long-run match between student and majors. In fact, high school peer composition may have simply generated a higher probability of mismatch driven by over-confidence, or imitation in males. Not only this did not result in more males graduating in PM majors, that are associated with higher wages, but it may have actually discouraged students and reduced their graduation rate. In the next section we analyze whether these negative college performance effects had a long-run impact on earnings of individuals 1 to 15 years into the labor market.

5.3 Earnings

By affecting, at least temporarily, their exposure to PM majors, but also the probability of graduating and the performance in college, the random gender composition of high school class could have affected individual performance in the long run. Are these effects still discernible on the labor market? Is there still a measurable effect of prevalently male high school classes on the earnings of males in the labor market, five to twenty years after they graduated from high school? Looking at the results so far, the effects could be positive for having increased the probability of exposure, at least for a while, to majors such as Engineering and Business. However they may also be negative, for having reduced performance and probability of graduation. In this section we tackle this question. We consider as outcomes the earnings of the individuals obtained from the Italian internal revenue service in year 2005 and matched to individuals based on their name and place of birth. We consider all individuals graduated from high school between 1985 and 2000 and hence on the labor market from 1 to 15 years. As long as they were still in Italy at that date, and received any income, their record was with the Internal revenue Service. Panel A of Table 10 shows the estimates using total log earnings as dependent variable. This would capture the long-run effect combining the increased PM Major enrollment and the worse academic performance due to mismatch. Then, in the lower panel B we only consider the "major of enrollment" of an individual and we simply associate to the major of enrollment the average earning for that major in our sample. Such variable allows us to isolate in term of earnings the impact of enrollment major choice, assuming however, that the individuals graduated from it at the average rate (which we know from table 9 not to be true) and went on to earn the average wage in the major. It is a way to isolate in terms of wages the pure effect of PM major exposure. The dependent variable is logarithm of earnings (both in Panel A and B) and so the coefficient represents a percentage change in earnings.

The results reported in Panel A do not show any significant coefficient on the >90% male variable. While the point estimates are positive on average, they are very noisy. Potentially, being in a >90% male class exposed students more frequently to PM majors (that generate high paying expertise) but then worsened the outcomes of their college career (that hurts earning potential), the two effects cancel out. For women we do not find any effect either. Certainly observing only total earning and only at one point in time after graduation reduces the ability of analyzing more in depth labor market outcomes, however, there is no sign of a persistent effect.

Considering the wage effect of major of enrollment only, isolated in the estimates of Panel B, male students in prevalently male classes have higher expected potential earnings (if they graduate in them and has the average wage performance within them) of about 8%. If we only observed enrollment in those majors for the male students analyzed (and not their performance, completion and then wages) we would be tempted to infer potentially beneficial effects of high school class gender composition. The more thorough analysis we are able to perform, however, shows that the long-run peer effects are much less significant than the effect on choice measured in the short-run. The peer effect can be in place when in the group, but the skills and abilities of an individuals may be the more fundamental determinants of their choices and of their long-run consequences.

6 Checks and Channels

In this section we test some potential channels and we suggest possible explanations for the peer-gender effects on the major choice of males that we established in the previous sections. As we found consistently only effects on males we limit our analysis to the male sample. First, we confirm that the peer-gender effect does not work through the student academic motivation or quality. Table 11, specification (1) shows the estimate of the coefficient of the dummy >90% males in the class on the high school exit score and reveals a minuscule and not statistically significant effect.

The second specification of Table 11 shows a very demanding check on the main effect that the >90% share of male classes affect the probability of PM major choice. In particular in that regression we consider only siblings in our dataset (identified by the same last name and common address) and we include family fixed effects, school effects and the usual individual controls. In this case the result is identified only on the different choice of male siblings graduating from the same high school within a family, which therefore share exactly the same socioeconomic background. The fact that we are restricting our sample to male siblings only, implies that the sample size is decreased by a factor of 8, from almost 10,000 to 1,300. The point estimate of the effect is 14.7 percentage points, very close to the main estimate in Table 6, Column (7) that was equal to 13.1. However, the standard error is more than double and hence the coefficient is not significant. Nevertheless the almost unchanged point estimate and the extreme demanding nature of the check convey the idea that classes with >90% male share can be associated with a shift of 13-14 points in the percent probability of attending a PM major by men.

In column (3) we use information from the survey about non academic activity of students. The dependent variable is a dummy equal to one if the student practiced sport in competitive form during high school. The prevalently male environment could have encouraged typically male behavior in other aspects of the student life (besides the choice of major). We do not find, however, that sport activities, typically pursued outside the high school environment in Italy, and more common for men than for women in our sample, increased for males exposed to prevalently male classes. This regression was performed only on those individuals randomly drawn in the telephone survey and hence the sample is only 1,173 individuals.

Besides a direct effect of peers on each others, the same group of teachers may relate differently to a class that is prevalently male. In the last 2 columns of Table 11 we pursue this idea. Our database contains, for a large number of students, the recommendations for college major given by the teachers, at the same time that they produced the final score for the student. Teachers, together with a final assessment on the skills of the students, suggested one or a set of college majors that they though most appropriate. These suggestions should reflect an assessment of skills and of the appropriate match, as seen by teachers. If they are genuinely based only on the students' skills they should be totally independent of the class gender composition. We coded these suggestions and in column (4) we use them as outcome variables. We see that, while the significance is only 12%, the teacher recommendation are also shifted in the same direction and by a similar amount towards PM majors for males in classes with >90% male share. Prevalently male classes encourage teachers towards stereotypical male major recommendations. It may be because teachers consider a smaller range of recommendation in a homogeneously male class, or because they perceive a stronger preference towards PM majors from the students. In any case their recommendation are also skewed. Even more interestingly, in the last column (5), we consider the actual PM major choice dummy as dependent variable and we control for the recommended PM dummy. We see that the recommended dummy has a very strong explanatory power and significance. We also see that once we control for teacher recommendation the effect of >90% male share decreases by more than half (to only to 5.8 percentage points) and it is no longer significant. It appears that the same group of teachers, when interacting with a prevalently male class, is more inclined to suggest to marginal (uncertain) males to go for a PM major. Or it could be that teachers in their non binding major suggestions, simply reflect the preferences of the student, known from interactions and conversations in class. It is interesting, however, that professors do not attenuate the (over)-tendency of male students to choose PM majors in prevalently male class, but if anything, they reinforce it.

7 Discussion and Conclusions

This paper has found a significant tendency of males in prevalently male high school classes to choose typically male college majors. This confirms the relevance of peers as factor affecting choices and attitudes of students. However it has also found, by following students along their college career, that this increased pressure to choose PM majors may have caused mismatches between skills and majors for marginal students who would have otherwise chosen less prestigious and less demanding majors. In the long run, students from prevalently male classes, undid the PM major choice and, as a result of mismatch, they ended up with lower performance in college and lower probability of graduating.

We can speculate about what drives these results and why they are not found for women. On one hand there is significant evidence that women choose less frequently math-intensive and prestigious school tracks, relative to men, in large part because they tend to shy away from highly competitive environments (e.g. Buser et al, forthcoming). We can hypothesize that an all male environment encourages this over-confidence in males, while an all female environment is not enough to boost confidence in women. The interesting finding of our analysis, however, is that this boost of confidence in males affects choices but not the academic ability and therefore increases mismatches and does not result in better outcomes. This confirms previous analysis that peer-pressure may result in mismatched choices (De Georgi et al. 2010). Alternatively, the effect on men may be linked to higher risk-aversion of women who are not willing to modify their choices in the light of peer choice, perceiving higher uncertainty for deviating from the median choice of female classmates. Males to the contrary may underestimate the consequences of a negative impact of mismatch and be more readily affected. Differences in risk aversion, however have been shown to explain only small part of differences in college major choice (Niederle and Vesterlund, 2007).

Overall we think that the results of our analysis constitute a cautionary tale on two important points. First, we show that PM majors are associated with higher wages and that, based on correlations alone, one would expect a higher wage and better labor market performance, by shifting (randomly) some people from non-PM to PM majors. This wage gain, however, does not take place in our analysis. Peer composition influences (exogenously) the choice of PM majors for males, but in the long run, the mismatch produces a negative effect on college performance and no effect on wages. Second, in the debate on the effects of peers in school, so far focussed on outcomes and performances while in school, we emphasize the importance of looking at long-run effects and to final outcomes. Further research is needed to shed more light on both these issues, and we hope this papers encourages similar data collections and research analysis in other countries and environments.

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Figures

Figure 1: Annual Earnings and female shares by major

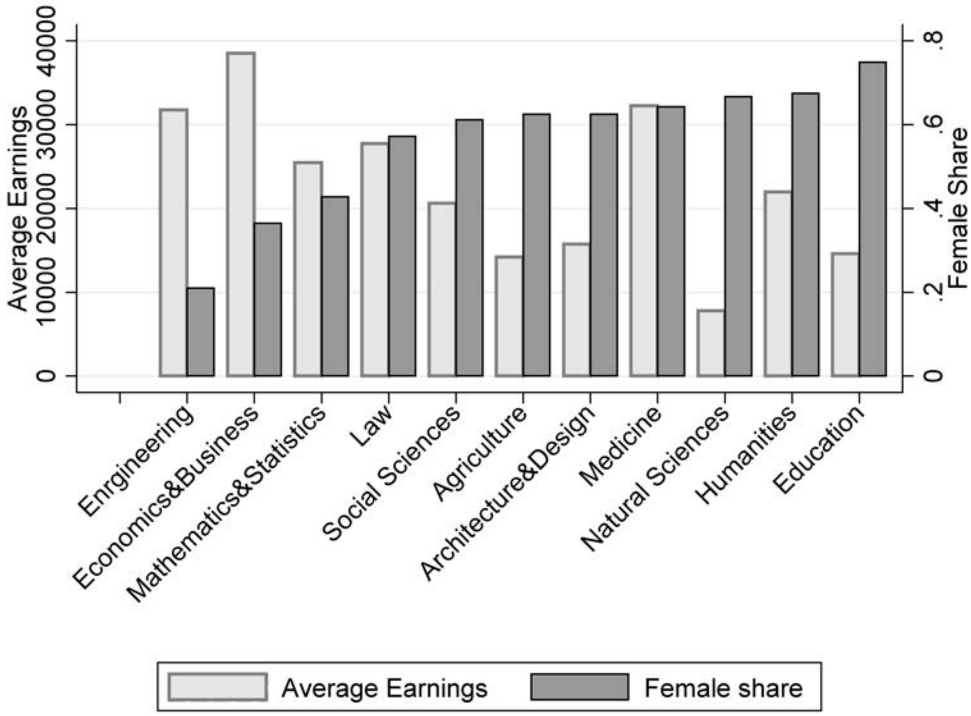


Figure 2: Observed female share distribution vs. simulated normal distribution

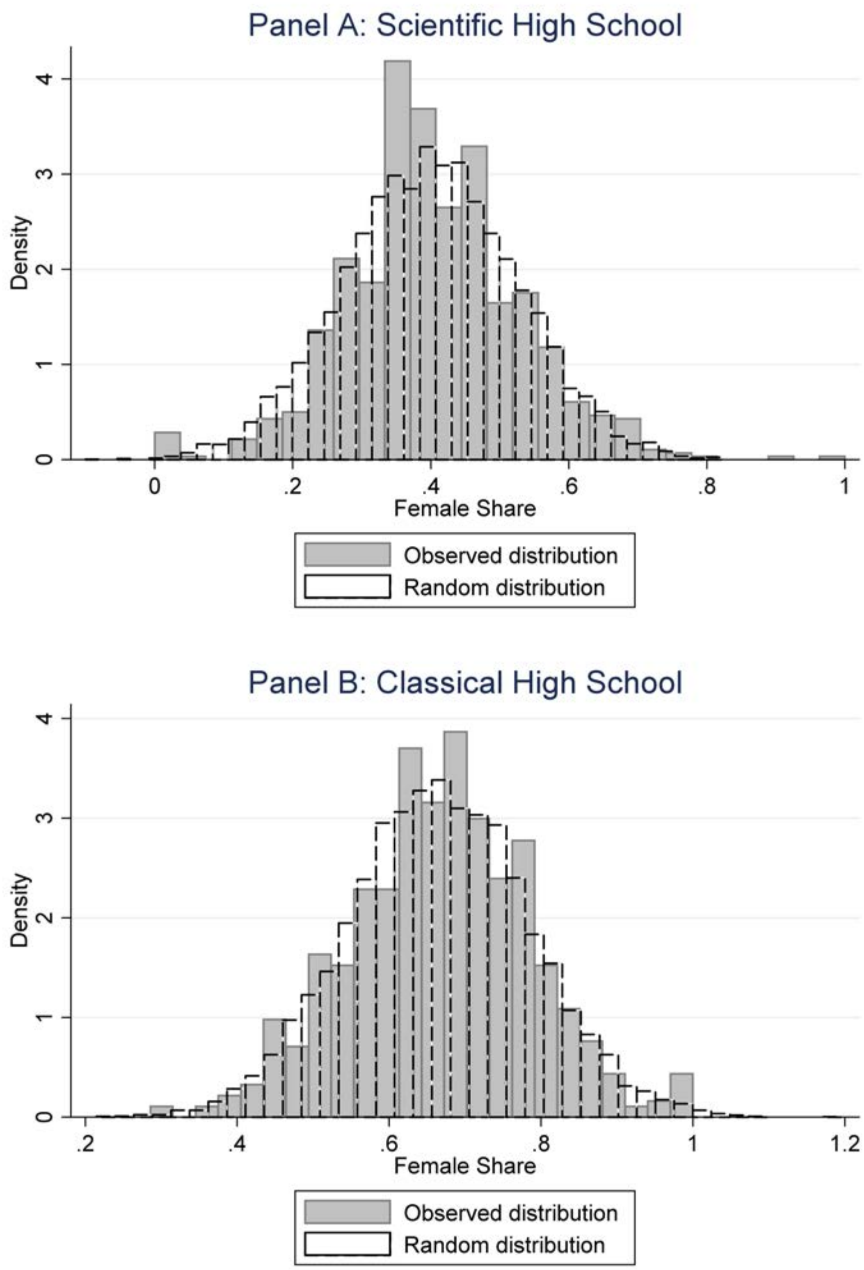
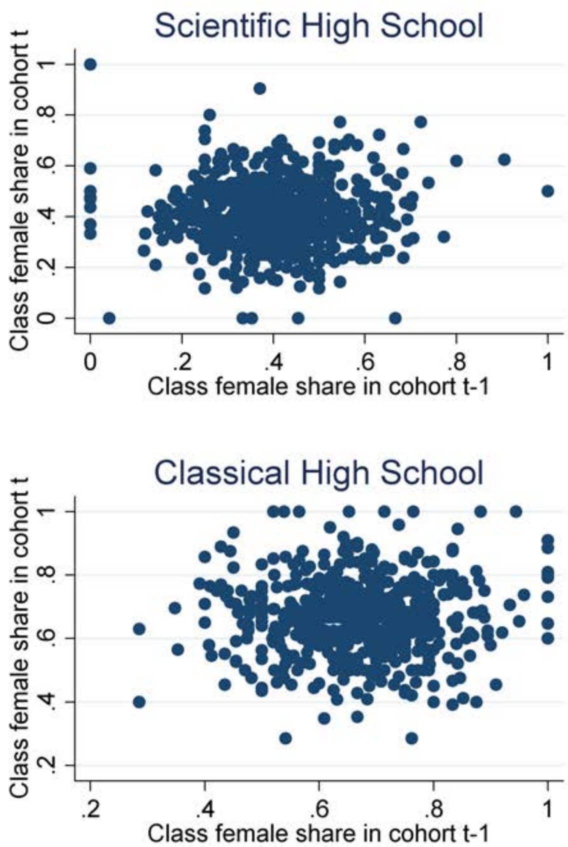


Figure 3: Auto-correlation of female share across graduating classes, within school-section



Tables

Table 1: Summary Statistics

Variable	Obs	Mean	All Std.Dev.	Min	Max	Women Mean	Men Mean	Difference | T-stat |
Individual Variables:								
Female	29370	0.523	0.499					
High School Variables:								
High school exit standardized score	29370	0.416	0.299	0	1	0.435	0.395	11.4
Within school/cohort rank	29370	0.495	0.313	0	1	0.516	0.471	12.4
College Variables:								
Enrolled in Prevalently Male majors	23118	0.275	0.447	0	1	0.423	0.139	50.3
Graduated in Prevalently Male majors	23118	0.215	0.411	0	1	0.320	0.118	39.0
Prevalently Male majors dropout	6362	0.229	.420	0	1	0.250	0.172	6.92
College time to graduation	16193	79.669	26.156	0	1	80.994	78.531	6.0
College exit score	16144	0.822	0.173	0	1	0.778	0.860	30.25
Pre-treatment Variables:								
Log(house value)	22365	7.992	0.298	7.409	9.143	7.988	7.998	2.2
Outcome Variables:								
Log(wage)	17004	9.679	1.279	0.693	13.746	9.461	9.906	22.0
Top Occupation	2957	0.367	0.482	0	1	0.308	0.432	7.10
High School Class Variables:								
Class size	1371	21.432	3.801	10	35			
Female share	1371	0.522	0.181	0	1			
Average high school exit score	1371	0.419	0.104	0.118	0.780			
Average log(House Value)	1219	7.982	0.161	7.606	8.477			
% students in bottom decile of house value distribution	1219	0.094	0.105	0	1			
% students in top decile of house value distribution	1219	0.082	0.107	0	0.57			

Table 2: Major Choice and Earnings

VARIABLES	(1) Females Log(wage)	(2) Males Log(wage)	(3) Log(wage)	(4) Log(wage)
(Female=1)			-0.401***	-0.251***
			(0.031)	(0.031)
(Graduated in PM majors=1)	0.647***	0.549***		0.578***
	(0.043)	(0.043)		(0.031)
(Graduated in PF majors=1)	-0.260***	-0.541***		-0.335***
	(0.043)	(0.068)		(0.037)
H.S. exit score	0.161**	-0.078	0.391***	0.036
	(0.070)	(0.063)	(0.042)	(0.044)
College exit score	0.633***	0.890***	0.039	0.781***
	(0.125)	(0.111)	(0.073)	(0.084)
(House value in top 10%=1)	0.095	0.026	0.089*	0.068
	(0.061)	(0.065)	(0.048)	(0.047)
(House value in bottom 10%=1)	-0.047	-0.062	-0.090**	-0.052
	(0.058)	(0.051)	(0.043)	(0.040)
(Commuting into city=1)	0.009	0.086	0.044	0.041
	(0.060)	(0.065)	(0.046)	(0.044)
Constant	9.411***	9.812***	10.304***	9.703***
	(0.103)	(0.091)	(0.060)	(0.069)
Observations	4,768	4,438	9,206	9,206
R-squared	0.233	0.311	0.224	0.269
School X Cohort FE	X	X	X	X

Method: OLS, Standard errors clustered at school/cohort level in parenthesis, *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Sample: Students graduated from high school between 1985 and 2000 and completing college.
Specifications: (1) Female students only. (2) Male students only. (3),(4) both male and female students.
Dependent variable: logarithm of personal income, as revealed to the internal revenue service in year 2005.
Independent variables: For all specifications School/Cohort fixed effects, high school exit score re-scaled between 0 and 1, college exit score (composite of G.P.A. and a score for dissertation) re-scaled between 0 and 1, dummy=1 if student used to live in a house in top (and another dummy for bottom) 10% of house value distribution, dummy=1 if student used to commute from outside the city. For specifications (3) and (4) a dummy=1 if student is female.
Definitions: Following statistics computed on our sample we define Prevalently Female (PF) Majors to be Humanities and Education, Prevalently Male (PM) Majors to be Engineering, Economics & Business. The omitted variable is Gender Balanced (GB) Majors which includes all residual fields of study.

Table 3: Female share and Classroom characteristics

VARIABLES	(1) Female share	(2) All females	(3) All males	(4) Female >90%	(5) Male >90%	(6) Female >75%	(7) Male >75%
Class share top 10% wealth	0.046	0.025	0.033	-0.014	0.031	0.196	-0.024
	(0.102)	(0.040)	(0.033)	(0.097)	(0.033)	(0.346)	(0.117)
Class share bot 10% wealth	0.056	0.053	0.023	0.148	0.030	-0.216	-0.029
	(0.062)	(0.047)	(0.023)	(0.091)	(0.036)	(0.352)	(0.115)
Class mean log house value	-0.090	-0.008	-0.034	-0.115	-0.013	-0.141	-0.080
	(0.125)	(0.016)	(0.035)	(0.101)	(0.016)	(0.420)	(0.172)
Class Size in Bottom 25%	0.005	-0.004	-0.013	0.008	-0.017	0.022	0.016
	(0.015)	(0.010)	(0.014)	(0.017)	(0.015)	(0.032)	(0.049)
Class Size in Top 25%	-0.014	-0.005	-0.001	-0.008	-0.006	-0.050	-0.000
	(0.015)	(0.005)	(0.001)	(0.011)	(0.006)	(0.062)	(0.021)
Class mean distance from school	-0.003	-0.003	-0.000	-0.003	-0.002	0.017	-0.006
	(0.006)	(0.003)	(0.004)	(0.014)	(0.003)	(0.012)	(0.008)
Class geo. concentration	0.040	0.012	0.013	0.038	-0.015	0.046	-0.199
	(0.063)	(0.041)	(0.081)	(0.084)	(0.058)	(0.151)	(0.145)
Constant	1.423	0.077	0.273	0.903	0.115	1.426	0.680
	(1.030)	(0.126)	(0.279)	(0.863)	(0.140)	(3.435)	(1.416)
Observations	1,219	1,219	1,219	1,219	1,219	1,219	1,219
R-squared	0.721	0.443	0.338	0.418	0.383	0.539	0.374
School X Cohort FE	X	X	X	X	X	X	X
School X Teachers X 5yrs FE	X	X	X	X	X	X	X

Method: OLS, Standard errors clustered at school level in parenthesis, *** p<0.01, ** p<0.05, * p<0.1.
Sample: Each observation corresponds to one class.
Dependent variable: Class female share for specification (1), a dummy=1 for all-female classes in (2) and one for all-male classes in (3). In specifications (4) and (5) a dummy=1 if classes respectively have more than 90% females and more than 90% males. (6)-(7) a dummy=1 if classes respectively have more than 75% females and more than 75% males.
Independent variables: Class share of students who used to live in a house valued in top decile of the house value distribution, class share of students who used to live in a house valued in top decile of the house value distribution, class average logarithm of market value of the house where the students used to live at the time they attended high school, a dummy for class size in the bottom 25% of observed class size distribution and one for class size in top 25%, class mean linear distance from school, class geographical concentration (measured as Herfindhal index of concentration in city-blocks). School/cohort fixed effects, group of teachers fixed effects every five years are also included (i.e. school-section fixed effects every five years).

Table 4: Auto-correlation of class female share within school-section

Dependent variable: High School Class Female Share

VARIABLES	(1)	(2)	(3)
Class female share t-1	0.022	0.036	-0.058
	(0.046)	(0.056)	(0.047)
Constant	0.650***	0.663***	0.723***
	(0.030)	(0.041)	(0.032)
Observations	1,268	1,268	1,268
R-squared	0.537	0.609	0.648
School FE	X		
SchoolXCohort FE		X	X
SchoolXTeachers FE			X

Method: OLS, Standard errors clustered at school level in parenthesis, *** p<0.01, ** p<0.05, * p<0.1
Sample: Each observation corresponds to one graduating class of a given school in a given year
Dependent variable: Female share in high school class graduating in year *t* within school-section (i.e. within group of teachers)
Independent variable: Female share in high school class graduating in year *t-1* within school-section (i.e. within group of teachers)

Table 5: School-Cohort female share and class gender composition

VARIABLES	(1) Female Share	(2) All Females	(3) All Males	(4) Females >90%	(5) Males >90%	(6) Females >75%	(7) Males >75%
School/Cohort Female Share	0.969***	0.130	-0.070	0.427*	-0.073	1.271**	-0.385*
	(0.037)	(0.167)	(0.085)	(0.209)	(0.084)	(0.446)	(0.175)
Class share top 10% wealth	0.041	-0.004	0.036	-0.031	0.041	0.252	-0.033
	(0.084)	(0.009)	(0.037)	(0.066)	(0.042)	(0.317)	(0.077)
Class share bot 10% wealth	0.047	0.032	0.024	0.078	0.023	-0.321	-0.064
	(0.047)	(0.032)	(0.021)	(0.084)	(0.027)	(0.305)	(0.128)
Class mean log house value	-0.080	-0.006	-0.046	-0.041	-0.024	-0.011	-0.085
	(0.099)	(0.018)	(0.035)	(0.090)	(0.026)	(0.354)	(0.154)
Class Size in Bottom 25%	0.004	-0.004	-0.014	0.002	-0.016	0.017	0.014
	(0.012)	(0.008)	(0.013)	(0.016)	(0.013)	(0.025)	(0.041)
Class Size in Top 25%	-0.010	-0.007	-0.002	-0.015	-0.005	-0.073	-0.007
	(0.011)	(0.007)	(0.002)	(0.011)	(0.006)	(0.043)	(0.016)
Class mean distance from school	-0.003	-0.002	-0.002	-0.003	-0.003	0.008	-0.005
	(0.005)	(0.002)	(0.004)	(0.012)	(0.004)	(0.012)	(0.007)
Class geo. concentration	0.028	-0.029	-0.046	-0.052	-0.073	-0.064	-0.199
	(0.058)	(0.044)	(0.112)	(0.077)	(0.100)	(0.155)	(0.155)
Constant	0.644	-0.014	0.414	-0.410	0.267	0.386	1.093
	(0.793)	(0.196)	(0.305)	(0.674)	(0.266)	(2.851)	(1.361)
Observations	1,196	1,196	1,196	1,196	1,196	1,196	1,196
R-squared	0.714	0.316	0.260	0.303	0.311	0.464	0.293
School Fixed Effects	X	X	X	X	X	X	X
School X Teachers X 5yrs FE	X	X	X	X	X	X	X
Cohort FE	X	X	X	X	X	X	X

Method: OLS, Standard errors clustered at school level in parenthesis, *** p<0.01, ** p<0.05, * p<0.1.
Sample: Each observation corresponds to one class.
Dependent variables: Class female share for specification (1), a dummy=1 for all-female classes in (2) and one for all-male classes in (3). In specifications (4) and (5) a dummy=1 if classes respectively have more than 90% females and more than 90% males. (6)-(7) a dummy=1 if classes respectively have more than 75% females and more than 75% males.
Independent variable: Female share of full cohort within school
Controls: Class share of students who used to live in a house valued in top decile of the house value distribution, class share of students who used to live in a house valued in top decile of the house value distribution, class average logarithm of market value of the house where the students used to live at the time they attended high school, a dummy for class size in the bottom 25% of observed class size distribution and one for class size in top 25%, class mean linear distance from school, class geographical concentration (measured as Herfindhal index of concentration in city-blocks). School/cohort fixed effects, group of teachers fixed effects every five years are also included (i.e. school-section fixed effects every five years).

Table 6: The effect of high-school class gender composition on students' major choice

	Females				Males			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Explanatory Variables →	Same Gender Share	Same Gender Share =100%	Same Gender Share >90%	Same Gender Share <10%	Same Gender Share	Same Gender Share =100%	Same Gender Share >90%	Same Gender Share <10%
Dependent Variable ↓								
Panel A: Prevalently Male (PM) major choice at first college enrollment=1								
(PM Major=1)	0.001	0.050	0.021	-0.044	0.026	0.086**	0.131***	-0.085
	(0.032)	(0.041)	(0.039)	(0.094)	(0.044)	(0.039)	(0.049)	(0.062)
Dep. var. mean	0.139	0.139	0.139	0.139	0.427	0.427	0.427	0.427
Panel B: Gender Balanced (GB) major choice at first college enrollment=1								
(GB Major=1)	0.060	-0.024	-0.033	0.044	-0.019	-0.079*	-0.105**	0.028
	(0.045)	(0.052)	(0.038)	(0.157)	(0.050)	(0.041)	(0.045)	(0.066)
Dep. var. mean	0.586	0.586	0.586	0.586	0.460	0.460	0.460	0.460
Panel C: Prevalently Female (PF) major choice at first college enrollment=1								
(PF Major=1)	-0.061	-0.027	0.012	-0.000	-0.007	-0.007	-0.026	0.058
	(0.041)	(0.053)	(0.053)	(0.113)	(0.028)	(0.011)	(0.016)	(0.073)
Dep. var. mean	0.275	0.275	0.275	0.275	0.113	0.113	0.113	0.113
Observations	10,318	10,318	10,318	10,318	9,773	9,773	9,773	9,773
Individual Controls:								
Cohort ranking	X	X	X	X	X	X	X	X
Fam. wealth proxy	X	X	X	X	X	X	X	X
Class-level controls:								
Size	X	X	X	X	X	X	X	X
Geo. Concentration	X	X	X	X	X	X	X	X
Fam. wealth proxy	X	X	X	X	X	X	X	X
SchoolXCohort FE	X	X	X	X	X	X	X	X
TeachersX5yrs FE	X	X	X	X	X	X	X	X

Method: OLS, Standard errors clustered at school/cohort level in parenthesis, *** p<0.01, ** p<0.05, * p<0.1. Specifications (1)-(4) on women only. (5)-(8) on men only.
Sample: high school graduates enrolling in college.
Dependent variables: In panel A dummy=1 if student enrolled in Engineering, Economics and Business at first college enrollment. In panel B a dummy=1 if student enrolled in Natural Sciences, Mathematics, Statistics, Computer Sciences, Medicine, Agriculture, Architecture, Design, Social Sciences or Law. In panel C a dummy=1 if student enrolled in Humanities or Education.
Treatment: In spec. (1) and (5) share of same gender classmates (i.e. for spec. 1 female share and for 4 male share), in (2) and (6) dummy for fully segregated classes (all-female and all-male), in (3) and (7) a dummy for classes with more than 90% of same gender classmates, in (4) and (8) a dummy for classes with less then 10% of same gender classmates.
Individual Controls: Within school/cohort ranking, dummy=1 if student used to live in a house in top (and another dummy for bottom) 10% of house value distribution, dummy=1 if student used to commute from outside the city.
Class-level controls: dummy=1 if class size in the bottom 25% and one for class size in top 25%, class geographical concentration (measured as Herfindhal index of concentration in city-blocks), Class share in bottom 10% of house value, Class share in top 10% of house value, School/cohort fixed effects, Group of teachers fixed effects every five years (i.e. school-section fixed effects every five years).

Table 7: Effect on major choice by academic quality

	Females			Males		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample→	All	Bot Qual	Top Qual	All	Bot Qual	Top Qual
Explanatory Var.↓						
	Panel A - Dep. Var.: (PM major=1)					
Same Gender Share>90%	0.021	0.076**	0.041	0.131***	0.465***	0.121
	(0.039)	(0.038)	(0.055)	(0.049)	(0.135)	(0.081)
Dep. var. mean	0.139	0.057	0.225	0.427	0.255	0.571
	Panel B - Dep, Var.: (GB major=1)					
Same Gender Share>90%	-0.033	-0.090	-0.049	-0.105**	-0.325**	-0.150**
	(0.038)	(0.077)	(0.102)	(0.045)	(0.150)	(0.070)
Dep. var. mean	0.586	0.644	0.515	0.460	0.620	0.327
	Panel C - Dep. Var.: (PF major=1)					
Same Gender Share>90%	0.012	0.014	0.008	-0.026	-0.140***	0.029
	(0.053)	(0.094)	(0.092)	(0.016)	(0.053)	(0.036)
Dep. var. mean	0.275	0.299	0.260	0.113	0.125	0.102
Observations	10,318	2,100	3,075	9,773	1,973	2,864
Individual Controls:						
Cohort ranking	X	X	X	X	X	X
Fam. wealth proxy	X	X	X	X	X	X
Class-level controls:						
Size	X	X	X	X	X	X
Geo. Concentration	X	X	X	X	X	X
Fam. wealth proxy	X	X	X	X	X	X
SchoolXCohort FE	X	X	X	X	X	X
SXTeachersX5yrs FE	X	X	X	X	X	X

Method: OLS, Standard errors clustered at school/cohort level in parenthesis, *** p<0.01, ** p<0.05, * p<0.1. Specification (1) on women only. Specification (2) on women in the bottom quartile of the within school/cohort/gender rank in high school exit score, (3) women in the top quartile of the same distribution. Specification (4) on men only. Specification (5) on men in the bottom quartile of the within school/cohort/gender rank in high school exit score, (6) men in the top quartile of the same distribution.
Sample: High school graduates enrolling in college.
Dependent variables: In panel A dummy=1 if student enrolled in Engineering, Economics and Business at first college enrollment. In panel B a dummy=1 if student enrolled in Natural Sciences, Mathematics, Statistics, Computer Sciences, Medicine, Agriculture, Architecture, Design, Social Sciences or Law. In panel C a dummy=1 if student enrolled in Humanities or Education.
Treatment: Dummy for classes with more than 90% of same-gender classmates.
Individual Controls: Within school/cohort ranking, dummy=1 if student used to live in a house in top (and another dummy for bottom) 10% of house value distribution, dummy=1 if student used to commute from outside the city.
Class-level controls: dummy=1 if class size in the bottom 25% and one for class size in top 25%, class geographical concentration (measured as Herfindhal index of concentration in city-blocks), Class share in bottom 10% of house value, Class share in top 10% of house value, School/cohort fixed effects, Group of teachers fixed effects every five years (i.e. school-section fixed effects every five years).

Table 8: Effect on major choice by parents' house value

	Females			**Males**		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample→	All	Low House Value	High House Value	All	Low House Value	High House Value
Explanatory Var.↓						
	Panel A - Dep. Var.: (PM major=1)					
Same Gender Share>90%	0.021	0.027	0.111	0.131***	0.247***	0.016
	(0.039)	(0.110)	(0.073)	(0.049)	(0.071)	(0.075)
Dep. var. mean	0.139	0.145	0.137	0.427	0.443	0.426
	Panel B - Dep, Var.: (GB major=1)					
Same Gender Share>90%	-0.033	-0.098	0.016	-0.105**	-0.219***	0.126
	(0.038)	(0.165)	(0.094)	(0.045)	(0.072)	(0.099)
Dep. var. mean	0.586	0.588	0.587	0.460	0.447	0.460
	Panel C - Dep. Var.: (PF major=1)					
Same Gender Share>90%	0.012	0.071	-0.127	-0.026	-0.028	-0.142***
	(0.053)	(0.154)	(0.087)	(0.016)	(0.027)	(0.053)
Dep. var. mean	0.275	0.267	0.276	0.113	0.110	0.114
Observations	10,318	2,442	2,142	9,773	2,215	2,277
Individual Controls:						
Cohort ranking	X	X	X	X	X	X
Fam. wealth proxy	X	X	X	X	X	X
Class-level controls:						
Size	X	X	X	X	X	X
Geo. Concentration	X	X	X	X	X	X
Fam. wealth proxy	X	X	X	X	X	X
SchoolXCohort FE	X	X	X	X	X	X
SXTeachersX5yrs FE	X	X	X	X	X	X

Method: OLS, Standard errors clustered at school/cohort level in parenthesis, *** p<0.01, ** p<0.05, * p<0.1.
Specifications: Specification (1) on women only. Specification (2) on women whose families used to live in a house in the bottom quartile of house price distribution of Milan at the time of high school attendance, (3) women in the top quartile of the same distribution. Specification (4) on men only. Specification (5) on men whose families used to live in a house in the bottom quartile of house price distribution of Milan at the time of high school attendance, (6) men in the top quartile of the same distribution.
Sample: High school graduates enrolling in college.
Dependent variables: In panel A dummy=1 if student enrolled in Engineering, Economics and Business at first college enrollment. In panel B a dummy=1 if student enrolled in Natural Sciences, Mathematics, Statistics, Computer Sciences, Medicine, Agriculture, Architecture, Design, Social Sciences or Law. In panel C a dummy=1 if student enrolled in Humanities or Education.
Treatment: Dummy for classes with more than 90% of same-gender classmates.
Individual Controls: Within school/cohort ranking, dummy=1 if student used to live in a house in top (and another dummy for bottom) 10% of house value distribution, dummy=1 if student used to commute from outside the city.
Class-level controls: dummy=1 if class size in the bottom 25% and one for class size in top 25%, class geographical concentration (measured as Herfindhal index of concentration in city-blocks), Class share in bottom 10% of house value, Class share in top 10% of house value, School/cohort fixed effects, Group of teachers fixed effects every five years (i.e. school-section fixed effects every five years).

Table 9: Effect on college outcomes

	Females			Males		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample→	All	Bot Qual	Top Qual	All	Bot Qual	Top Qual
Explanatory Var.↓						
Panel A - Dep. Var.: (College Graduate=1) in first college spell						
Same Gender Share>90%	-0.022	-0.058	-0.002	-0.086**	-0.205	-0.095**
	(0.040)	(0.080)	(0.069)	(0.035)	(0.182)	(0.039)
Dep. var. mean	0.720	0.552	0.841	0.667	0.479	0.824
Panel B - Dep. Var.: (College Graduate=1)						
Same Gender Share>90%	-0.022	-0.143*	-0.003	-0.081***	-0.253	-0.092**
	(0.041)	(0.079)	(0.070)	(0.025)	(0.164)	(0.041)
Dep. var. mean	0.759	0.594	0.871	0.712	0.522	0.864
Panel C - Dep. Var.: (Ever graduated in PM Major=1)						
Same Gender Share>90%	0.010	-0.024	0.012	-0.048*	-0.030	-0.028
	(0.018)	(0.019)	(0.033)	(0.025)	(0.080)	(0.023)
Dep. var. mean	0.119	0.038	0.203	0.321	0.141	0.499
Observations	10,318	2,100	3,075	9,771	1,972	2,863
Panel D - Dep. Var.: Time to Graduation - first spell						
Same Gender Share>90%	1.414	-3.056	1.771	-0.603	9.209*	8.814
	(2.648)	(9.455)	(2.597)	(3.325)	(5.209)	(6.057)
Dep. var. mean	79.301	87.028	73.602	82.508	89.515	77.204
Observations	7,438	1,160	2,588	6,537	945	2,363
Panel E-Dep. Var.: College graduation score conditional on time to graduation						
Same Gender Share>90%	-0.024**	-0.090*	-0.020	-0.026**	-0.135***	-0.037
	(0.012)	(0.048)	(0.021)	(0.011)	(0.023)	(0.034)
Dep. var. mean	0.860	0.764	0.926	0.780	0.689	0.853
Observations	7,416	1,149	2,584	6,511	941	2,359
Individual Controls:						
Cohort ranking	X	X	X	X	X	X
Fam. wealth proxy	X	X	X	X	X	X
Class-level controls:						
Size	X	X	X	X	X	X
Geo. Concentration	X	X	X	X	X	X
Fam. wealth proxy	X	X	X	X	X	X
SchoolXCohort FE	X	X	X	X	X	X
SXTeachersX5yrs FE	X	X	X	X	X	X
College controls:						
Major FE	X	X	X	X	X	X
University FE	X	X	X	X	X	X

Method: OLS, Standard errors clustered at school/cohort level in parenthesis, *** p<0.01, ** p<0.05, * p<0.1. Specification (1) on women only. Specification (2) on women in the bottom quartile of the within school/cohort/gender rank in high school exit score, (3) women in the top quartile of the same distribution. Specification (4) on men only. Specification (5) on men in the bottom quartile of the within school/cohort/gender rank in high school exit score, (6) men in the top quartile of the same distribution.
Dependent variables: In panel A dummy=1 if individual completed the degree chosen at first college enrollment. In panel B dummy=1 if individual completed any college degree. In Panel C dummy=1 if individual ever completed one of Prevalently Male degree. Panel D time elapsed between high school graduation and completion of the degree chosen at first college enrollment (in months). In panel E college final score (computed as a weighted average of GPA and thesis evaluation and discussion) and conditional on time to graduation.
Treatment: Dummy for classes with more than 90% of same-gender classmates.
Individual Controls: Within school/cohort ranking, dummy=1 if student used to live in a house in top (and another dummy for bottom) 10% of house value distribution, dummy=1 if student used to commute from outside the city.
Class-level controls: dummy=1 if class size in the bottom 25% and one for class size in top 25%, class geographical concentration (measured as Herfindhal index of concentration in city-blocks), Class share in bottom 10% of house value, Class share in top 10% of house value, School/cohort fixed effects, Group of teachers fixed effects every five years (i.e. school-section fixed effects every five years).

Table 10: Effect on Annual Earnings

	Females			Males		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample→	All	Bot Qual	Top Qual	All	Bot Qual	Top Qual
Explanatory Var.↓						
Panel A - Dep. Var.: Log of Annual Earnings						
Same Gender Share>90%	-0.057	0.119	0.170	0.105	0.238	-0.081
	(0.141)	(0.406)	(0.309)	(0.074)	(0.257)	(0.093)
Dep. var. mean	9.422	9.207	9.617	9.849	9.651	10.008
Observations	6,508	1,279	1,999	6,587	1,303	1,933
Panel B - Dep. Var.: Log of expected annual earnings by major choice						
Same Gender Share>90%	-0.009	0.081	-0.042	0.084***	0.249***	0.107***
	(0.046)	(0.110)	(0.068)	(0.028)	(0.083)	(0.032)
Dep. var. mean	9.981	9.919	10.048	10.178	10.086	10.253
Observations	10,311	2,097	3,073	9,770	1,972	2,863
Individual Controls:						
Cohort ranking	X	X	X	X	X	X
Fam. wealth proxy	X	X	X	X	X	X
Class-level controls:						
Size	X	X	X	X	X	X
Geo. Concentration	X	X	X	X	X	X
Fam. wealth proxy	X	X	X	X	X	X
SchoolXCohort FE	X	X	X	X	X	X
SXTeachersX5yrs FE	X	X	X	X	X	X

Method: OLS, Standard errors clustered at school/cohort level in parenthesis, *** p<0.01, ** p<0.05, * p<0.1. Specification (1) on women only. Specification (2) on women in the bottom quartile of the within school/cohort/gender rank in high school exit score, (3) women in the top quartile of the same distribution. Specification (4) on men only. Specification (5) on men in the bottom quartile of the within school/cohort/gender rank in high school exit score, (6) men in the top quartile of the same distribution.
Sample: high school students graduating before 2000 (5 years before wages are observed) and enrolling in college.
Dependent variables: In panel A logarithm of personal income, as revealed to the internal revenue service in year 2005. In panel B logarithm of personal income calculated on our sample and imputed by choice of major in first college enrollment.
Treatment: Dummy for classes with more than 90% of same-gender classmates.
Individual Controls: Within school/cohort ranking, dummy=1 if student used to live in a house in top (and another dummy for bottom) 10% of house value distribution, dummy=1 if student used to commute from outside the city.
Class-level controls: dummy=1 if class size in the bottom 25% and one for class size in top 25%, class geographical concentration (measured as Herfindhal index of concentration in city-blocks), Class share in bottom 10% of house value, Class share in top 10% of house value, School/cohort fixed effects, Group of teachers fixed effects every five years (i.e. school-section fixed effects every five years).

Table 11: Robustness specifications and alternative outcomes.

	Sample: Males only				
	(1)	(2)	(3)	(4)	(5)
Dep. Var.→	High School Exit Score	Family FE PMM=1	Sport=1	Teach recc. PMM=1	PMM=1
Explanatory Var.↓					
Same Gender Share>90%	0.002	0.147	-0.043	0.156	0.058
	(0.004)	(0.135)	(0.162)	(0.100)	(0.046)
(Teach. reccomend PMM=1)					0.462***
					(0.015)
Dep. var. mean	0.427	0.442	0.306	0.427	0.427
Observations	9,773	1,301	1,173	9,773	9,773
Individual Controls:					
Cohort ranking	X	X	X	X	X
Fam. wealth proxy	X	X	X	X	X
Class-level controls:					
Size	X	X	X	X	X
Geo. Concentration	X	X	X	X	X
Fam. wealth proxy	X	X	X	X	X
School FE	-	X	-	-	-
SchoolXCohort FE	X	-	X	X	X
SXTeachersX5yrs FE	X	-	X	X	X
Family Fe	-	X	-	-	-
Siblings Sample	-	X	-	-	-
Survey Sample	-	-	X	-	-

Method: OLS, Standard errors clustered at school/cohort level in parenthesis, *** p<0.01, ** p<0.05, * p<0.1.
Sample: Male high school students for all Specifications. In (2) sample restricted to siblings only. In (3) sample restricted to individuals randomly drawn for a phone interview.
Dependent variables: In specification (1) High school exit score re-scaled to be between 0 and 1. In (2) a dummy=1 if student enrolled in one of Prevalently Male Majors (Engineering, Economics and Business) at first college enrollment. In (3) a dummy=1 if individual practised sport at competitive level at the time of high school. In (4) a dummy=1 if teachers formally suggested the student to enroll in one of the Prevalently Male Majors. In (5) a dummy=1 if student enrolled in one of Prevalently Male Majors (Engineering, Economics and Business) at first college enrollment.
Treatment: Dummy for classes with more than 90% of same-gender classmates.
Individual Controls: Within school/cohort ranking, dummy=1 if student used to live in a house in top (and another dummy for bottom) 10% of house value distribution, dummy=1 if student used to commute from outside the city.
Class-level controls: for all specifications dummy=1 if class size in the bottom 25% and one for class size in top 25%, class geographical concentration (measured as Herfindhal index of concentration in city-blocks), Class share in bottom 10% of house value, Class share in top 10% of house value. For specifications (1), (3)-(5) School/cohort fixed effects, Group of teachers fixed effects every five years (i.e. school-section fixed effects every five years). For specifications (2) Family Fixed Effects, School fixed effects.

Appendix - Data Details

In this work we present for the first time a unique database collecting information on the high school career, university career and labor market performance of young Italians who have graduated from high school between 1985 and 2005. This dataset involves different sources that have been carefully matched in a complicated merging process. The collection of the database has involved the collaboration of many parties. The help from the following persons and institutions made the collection possible: the directors of the high schools in Milan, the company Ambroscuole the Provincia di Milano, Daniele Checchi (for Universta Statale), Carlo Lucifora (for Universita Cattolica), Francesco Peri (For Universita' di Milano, Bicocca), Augusto Sarti and Mauro Santomauro (for Politecnico di Milano). Davide Malacrino and Francesca Barbiero provided excellent assistance in collecting and organizing the data. We summarize the sources of the single datasets merged, the information contained in each dataset and the merging process in figure 10. The diagram representing the merging process must be read from left to right. The core dataset include the universe of all high school graduates attending college-prep schools in the city of Milan between 1985 and 2005 (around 30550 individuals). Data have been collected manually by inputting the information contained in hard copies of the school records. The list of the 13 college-prep high schools in the city of Milan involved in the data collection process by type of school (Classical Studies vs. Scientific Studies) is included in Table A.1.

Among the five major universities of Milan involved in the collection of our data, three are public universities (Universita' degli Studi di Milano, Universita' degli Studi di Milano Bicocca, Politecnico di Milano) and two are private (Universita' Bocconi, Universita Cattolica di Milano) . The first two public universities mentioned have a very broad offer of majors while Politecnico di Milano offers degrees in Engineering, Architecture and Design only. Among the private universities Universita Cattolica di Milano has a broad offer of majors comparable with Universita degli Studi di Milano while Universita Bocconi is a school of Business, Economics and Law. The list of majors offered overall by universities located in Milan is very large. For our analysis we thus aggregated all these majors in 11 broader Fields of Study as shown in Table A.2.

Appendix - Figures and Tables

Figure A1: Dataset Structure

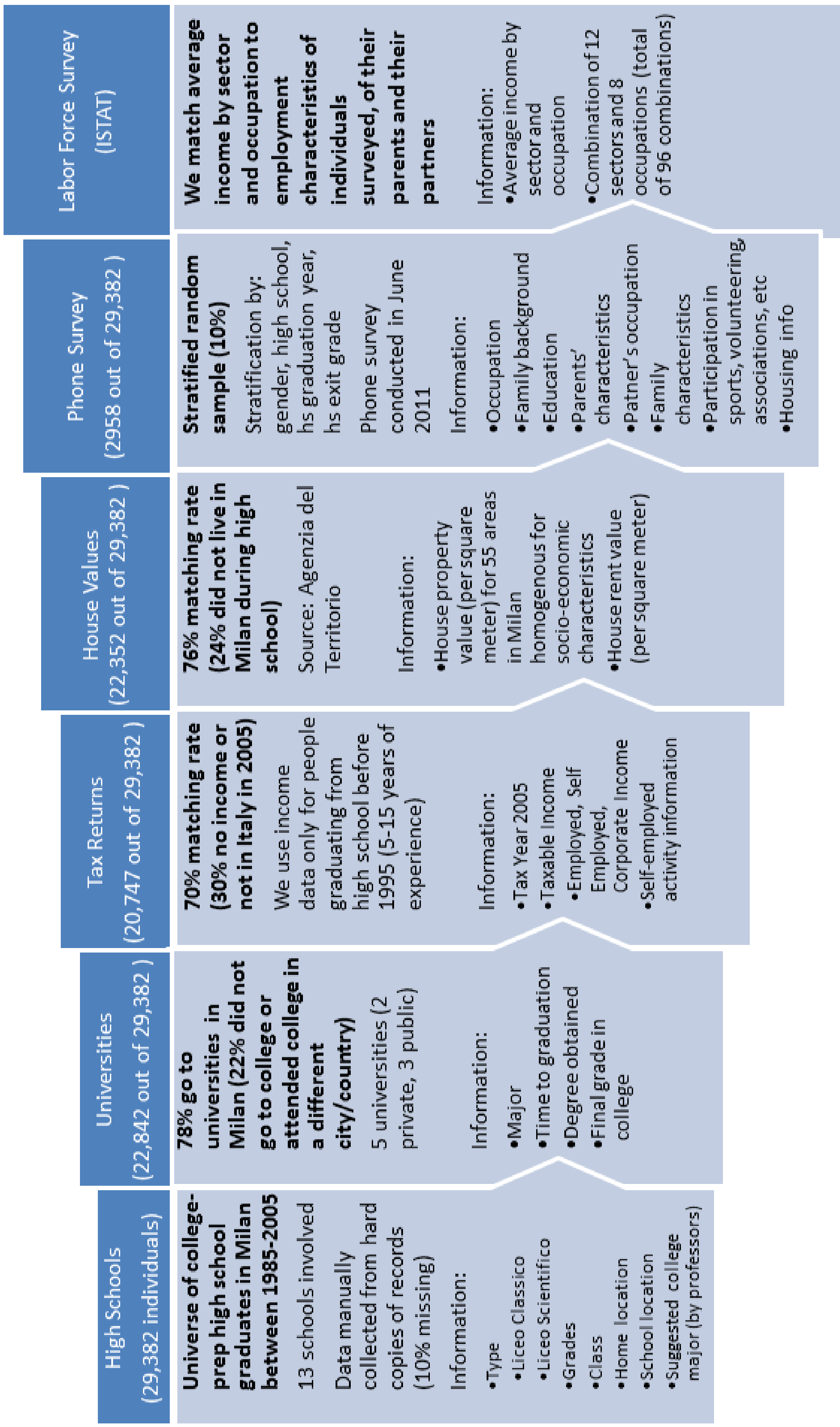


Table A1: Class assignment and pre-determined characteristics

VARIABLES	(1) Log house value	(2) Distance from school	(3) Prob house top 10%==1	(4) Prob house bottom 10%==1
Peers' mean log house value	0.024			
	(0.021)			
Cohort mean house value	-102.113***			
	(10.770)			
Peers' mean distance from school		0.003		
		(0.017)		
Cohort mean dist from school		-119.151***		
		(8.173)		
Class share in top 10% of house values			0.070	
			(0.044)	
Cohort share in top 10% of house values			-95.905***	
			(11.513)	
Class share in bottom 10% of house values				-0.031
				(0.044)
Cohort share in bottom 10% of house values				-95.916***
				(9.130)
Constant	791.336***	814.881***	9.783***	9.895***
	(82.639)	(55.528)	(1.151)	(0.913)
Observations	22,362	25,945	25,945	25,945
R-squared	0.827	0.839	0.371	0.350
School X Cohort FE	X	X	X	X
School X Group of Teachers X 5years FE	X	X	X	X

Method: OLS, Standard errors clustered at school/cohort level in parenthesis, *** p<0.01, ** p<0.05, * p<0.1.
Sample: High school students graduating between 1985 and 2005.
Dependent variable: for specification (1) the logarithm of market value of the house where the students used to live at the time they attended high school, for specification (2) linear distance from school to the house where the students used to live at the time they attended high school in meters, for specification (3) a dummy = 1 if the student used to live in a house valued in top decile of the house value distribution, for specification (4) a dummy = 1 if the student used to live in a house valued in top decile of the house value distribution.
Independent variables: for specification (1) class peers' and school/cohort peers' average logarithm of market value of the house where the students used to live at the time they attended high school, for specification (2) class peers' and school/cohort peers' linear distance from school to the house where the students used to live at the time they attended high school in meters, for specification (3) shares of class peers and school/cohort peers who used to live in a house valued in top decile of the house value distribution, for specification (4) shares of class peers and school/cohort peers who used to live in a house valued in top decile of the house value distribution. In all specifications school/cohort fixed effects, Group of teachers fixed effects every five year.

Table A2: Effect on major choice controlling for both individual and class average high school exit score rank.

	Females				Males			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Explanatory Variables →	Same Gender Share	Same Gender Only	Same Gender Share >90%	Same Gender Share <10%	Same Gender Share	Same Gender Only	Same Gender Share >90%	Same Gender Share <10%
Dependent Variable ↓								
Panel A: Prevalently Male (PM) major choice at first college enrollment=1								
(PM Major=1)	0.000	0.048	0.019	-0.045	0.028	0.086**	0.134***	-0.086
	(0.032)	(0.041)	(0.039)	(0.094)	(0.044)	(0.039)	(0.049)	(0.062)
Dep. var. mean	0.139	0.139	0.139	0.139	0.427	0.427	0.427	0.427
Panel B: Gender Balanced (GB) major choice at first college enrollment=1								
(GB Major=1)	0.061	-0.022	-0.032	0.045	-0.021	-0.079*	-0.108**	0.028
	(0.044)	(0.051)	(0.037)	(0.157)	(0.050)	(0.040)	(0.045)	(0.066)
Dep. var. mean	0.586	0.586	0.586	0.586	0.460	0.460	0.460	0.460
Panel C: Prevalently Female (PF) major choice at first college enrollment=1								
(PF Major=1)	-0.061	-0.026	0.013	0.000	-0.007	-0.007	-0.026	0.058
	(0.040)	(0.054)	(0.054)	(0.113)	(0.028)	(0.011)	(0.016)	(0.073)
Dep. var. mean	0.275	0.275	0.275	0.275	0.113	0.113	0.113	0.113
Observations	10,318	10,318	10,318	10,318	9,773	9,773	9,773	9,773
Individual Controls:								
Cohort ranking	X	X	X	X	X	X	X	X
Fam. wealth proxy	X	X	X	X	X	X	X	X
Class-level controls:								
Size	X	X	X	X	X	X	X	X
Geo. Concentration	X	X	X	X	X	X	X	X
Fam. wealth proxy	X	X	X	X	X	X	X	X
SchoolXCohort FE	X	X	X	X	X	X	X	X
SXTeachersX5yrs FE	X	X	X	X	X	X	X	X
Avg. female rank	X	X	X	X	-	-	-	-
Avg. male rank	-	-	-	-	X	X	X	X

Method: OLS, Standard errors clustered at school/cohort level in parenthesis, *** p<0.01, ** p<0.05, * p<0.1. Specifications (1)-(4) on women only. (5)-(8) on men only. This table replicates table 6 adding control for average high school outcome of class.
Sample: high school graduates enrolling in college.
Dependent variables: In panel A dummy=1 if student enrolled in Engineering, Economics and Business at first college enrollment. In panel B a dummy=1 if student enrolled in Natural Sciences, Mathematics, Statistics, Computer Sciences, Medicine, Agriculture, Architecture, Design, Social Sciences or Law. In panel C a dummy=1 if student enrolled in Humanities or Education.
Treatment: In spec. (1) and (5) share of same gender classmates (i.e. for spec. 1 female share and for 4 male share), in (2) and (6) dummy for fully segregated classes (all-female and all-male), in (3) and (7) a dummy for classes with more than 90% of same gender classmates, in (4) and (8) a dummy for classes with less then 10% of same gender classmates.
Individual Controls: Within school/cohort ranking, dummy=1 if student used to live in a house in top (and another dummy for bottom) 10% of house value distribution, dummy=1 if student used to commute from outside the city.
Class-level controls: dummy=1 if class size in the bottom 25% and one for class size in top 25%, class geographical concentration (measured as Herfindhal index of concentration in city-blocks), Class share in bottom 10% of house value, Class share in top 10% of house value, School/cohort fixed effects, Group of teachers fixed effects every five years (i.e. school-section fixed effects every five years). In columns (1)-(4) we control for the average within school/cohort/gender rank in the high school exit score of female students in the class. In (5)-(8) for the average within school/cohort/gender rank of male students in the class.

Table A3: Effect on major choice with no controls for individual and class average high school exit score rank

	Females				Males			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Explanatory Variables →	Same Gender Share	Same Gender Only	Same Gender Share >90%	Same Gender Share <10%	Same Gender Share	Same Gender Only	Same Gender Share >90%	Same Gender Share <10%
Dependent Variable ↓								
Panel A: Prevalently Male (PM) major choice at first college enrollment=1								
(PM Major=1)	-0.002	0.038	0.010	-0.056	0.030	0.109***	0.154***	-0.073
	(0.032)	(0.042)	(0.037)	(0.100)	(0.044)	(0.035)	(0.043)	(0.061)
Dep. var. mean	0.139	0.139	0.139	0.139	0.427	0.427	0.427	0.427
Panel B: Gender Balanced (GB) major choice at first college enrollment=1								
(GB Major=1)	0.062	-0.014	-0.024	0.053	-0.023	-0.101***	-0.127***	0.016
	(0.045)	(0.052)	(0.039)	(0.164)	(0.050)	(0.035)	(0.038)	(0.072)
Dep. var. mean	0.586	0.586	0.586	0.586	0.460	0.460	0.460	0.460
Panel C: Prevalently Female (PF) major choice at first college enrollment=1								
(PF Major=1)	-0.060	-0.024	0.015	0.002	-0.007	-0.008	-0.027	0.057
	(0.041)	(0.054)	(0.053)	(0.112)	(0.028)	(0.011)	(0.016)	(0.072)
Dep. var. mean	0.275	0.275	0.275	0.275	0.113	0.113	0.113	0.113
Observations	10,318	10,318	10,318	10,318	9,773	9,773	9,773	9,773
Individual Controls:								
Cohort ranking	-	-	-	-	-	-	-	-
Fam. wealth proxy	X	X	X	X	X	X	X	X
Class-level controls:								
Size	X	X	X	X	X	X	X	X
Geo. Concentration	X	X	X	X	X	X	X	X
Fam. wealth proxy	X	X	X	X	X	X	X	X
SchoolXCohort FE	X	X	X	X	X	X	X	X
SXTeachersX5yrs FE	X	X	X	X	X	X	X	X
Avg. class female rank	-	-	-	-	-	-	-	-
Avg. class male rank	-	-	-	-	-	-	-	-

Method: OLS, Standard errors clustered at school/cohort level in parenthesis, *** p<0.01, ** p<0.05, * p<0.1. Specifications (1)-(4) on women only. (5)-(8) on men only. This table replicates table 6 without controlling for individual performance in the high school exit exam, nor for average class performance.
Sample: high school graduates enrolling in college.
Dependent variables: In panel A dummy=1 if student enrolled in Engineering, Economics and Business at first college enrollment. In panel B a dummy=1 if student enrolled in Natural Sciences, Mathematics, Statistics, Computer Sciences, Medicine, Agriculture, Architecture, Design, Social Sciences or Law. In panel C a dummy=1 if student enrolled in Humanities or Education.
Treatment: In spec. (1) and (5) share of same gender classmates (i.e. for spec. 1 female share and for 4 male share), in (2) and (6) dummy for fully segregated classes (all-female and all-male), in (3) and (7) a dummy for classes with more than 90% of same gender classmates, in (4) and (8) a dummy for classes with less then 10% of same gender classmates.
Individual Controls: Dummy=1 if student used to live in a house in top (and another dummy for bottom) 10% of house value distribution, dummy=1 if student used to commute from outside the city.
Class-level controls: dummy=1 if class size in the bottom 25% and one for class size in top 25%, class geographical concentration (measured as Herfindhal index of concentration in city-blocks), Class share in bottom 10% of house value, Class share in top 10% of house value, School/cohort fixed effects, Group of teachers fixed effects every five years (i.e. school-section fixed effects every five years).

Table A4: The effect of gender segregated classes on major choice by academic quality

	Females			Males		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample→	All	Bot Qual	Top Qual	All	Bot Qual	Top Qual
Explanatory Var.↓						
	Panel A - Dep. Var.: (PM major=1)					
Same Gender Only	0.050	0.139***	0.049	0.086**	0.375***	0.058
	(0.041)	(0.039)	(0.060)	(0.039)	(0.125)	(0.073)
Dep. var. mean	0.139	0.057	0.225	0.427	0.255	0.571
	Panel B - Dep, Var.: (GB major=1)					
Same Gender Only	-0.024	-0.035	-0.050	-0.079*	-0.244	-0.105
	(0.052)	(0.053)	(0.138)	(0.041)	(0.149)	(0.072)
Dep. var. mean	0.586	0.644	0.515	0.460	0.620	0.327
	Panel C - Dep. Var.: (PF major=1)					
Same Gender Only	-0.027	-0.105***	0.001	-0.007	-0.131**	0.047
	(0.053)	(0.036)	(0.096)	(0.011)	(0.064)	(0.032)
Dep. var. mean	0.275	0.299	0.260	0.113	0.125	0.102
Observations	10,318	2,100	3,075	9,773	1,973	2,864
Individual Controls:						
Cohort ranking	X	X	X	X	X	X
Fam. wealth proxy	X	X	X	X	X	X
Class-level controls:						
Size	X	X	X	X	X	X
Geo. Concentration	X	X	X	X	X	X
Fam. wealth proxy	X	X	X	X	X	X
SchoolXCohort FE	X	X	X	X	X	X
SXTeachersX5yrs FE	X	X	X	X	X	X

Method: OLS, Standard errors clustered at school/cohort level in parenthesis, *** p<0.01, ** p<0.05, * p<0.1. Specification (1) on women only. Specification (2) on women in the bottom quartile of the within school/cohort/gender rank in high school exit score, (3) women in the top quartile of the same distribution. Specification (4) on men only. Specification (5) on men in the bottom quartile of the within school/cohort/gender rank in high school exit score, (6) men in the top quartile of the same distribution. This table replicates table 7 with single-gender classes as treatment instead of dummies for same-gender students above 90%.
Sample: high school graduates enrolling in college.
Dependent variables: In panel A dummy=1 if student enrolled in Engineering, Economics and Business at first college enrollment. In panel B a dummy=1 if student enrolled in Natural Sciences, Mathematics, Statistics, Computer Sciences, Medicine, Agriculture, Architecture, Design, Social Sciences or Law. In panel C a dummy=1 if student enrolled in Humanities or Education.
Treatment: Dummy for all-female classes in (1)-(3), dummy for all-male classes for (4)-(6).
Individual Controls: Within school/cohort ranking, dummy=1 if student used to live in a house in top (and another dummy for bottom) 10% of house value distribution, dummy=1 if student used to commute from outside the city.
Class-level controls: dummy=1 if class size in the bottom 25% and one for class size in top 25%, class geographical concentration (measured as Herfindhal index of concentration in city-blocks), Class share in bottom 10% of house value, Class share in top 10% of house value, School/cohort fixed effects, Group of teachers fixed effects every five years (i.e. school-section fixed effects every five years).

Table A5: Effect on major choice by academic quality (above/below median quality).

	Females			**Males**		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample→	All	Below Med Quality	Above Med Quality	All	Below Med Quality	Above Med Quality
Explanatory Var.↓						
	Panel A - Dep. Var.: (PM major=1)					
Same Gender Share>90%	0.021	-0.025	0.050	0.131***	0.240***	0.074
	(0.039)	(0.035)	(0.055)	(0.049)	(0.062)	(0.070)
Dep. var. mean	0.139	0.080	0.187	0.427	0.314	0.519
	Panel B - Dep, Var.: (GB major=1)					
Same Gender Share>90%	-0.033	0.045	-0.108**	-0.105**	-0.181***	-0.095*
	(0.038)	(0.050)	(0.054)	(0.045)	(0.068)	(0.056)
Dep. var. mean	0.586	0.630	0.549	0.460	0.565	0.375
	Panel C - Dep. Var.: (PF major=1)					
Same Gender Share>90%	0.012	-0.020	0.058	-0.026	-0.060**	0.020
	(0.053)	(0.063)	(0.065)	(0.016)	(0.026)	(0.022)
Dep. var. mean	0.275	0.290	0.264	0.113	0.121	0.107
Observations	10,318	4,641	5,677	9,773	4,393	5,380
Individual Controls:						
Cohort ranking	X	X	X	X	X	X
Fam. wealth proxy	X	X	X	X	X	X
Class-level controls:						
Size	X	X	X	X	X	X
Geo. Concentration	X	X	X	X	X	X
Fam. wealth proxy	X	X	X	X	X	X
SchoolXCohort FE	X	X	X	X	X	X
SXTeachersX5yrs FE	X	X	X	X	X	X

Method: OLS, Standard errors clustered at school/cohort level in parenthesis, *** p<0.01, ** p<0.05, * p<0.1. Specification (1) on women only. Specification (2) on women below the median of the within school/cohort/gender rank in high school exit score, (3) women above the median of the same distribution. Specification (4) on men only. Specification (5) on men below the median of the within school/cohort/gender rank in high school exit score, (6) men above the same distribution. This table replicates table 7 but stratifies the sample in below vs. above the quality distribution median instead for bottom and top quartile.
Sample: High school graduates enrolling in college.
Dependent variables: In panel A dummy=1 if student enrolled in Engineering, Economics and Business at first college enrollment. In panel B a dummy=1 if student enrolled in Natural Sciences, Mathematics, Statistics, Computer Sciences, Medicine, Agriculture, Architecture, Design, Social Sciences or Law. In panel C a dummy=1 if student enrolled in Humanities or Education.
Treatment: Dummy for classes with more than 90% of same-gender classmates.
Individual Controls: Within school/cohort ranking, dummy=1 if student used to live in a house in top (and another dummy for bottom) 10% of house value distribution, dummy=1 if student used to commute from outside the city.
Class-level controls: dummy=1 if class size in the bottom 25% and one for class size in top 25%, class geographical concentration (measured as Herfindhal index of concentration in city-blocks), Class share in bottom 10% of house value, Class share in top 10% of house value, School/cohort fixed effects, Group of teachers fixed effects every five years (i.e. school-section fixed effects every five years).