Scientific Education and Innovation:

From Technical Diplomas to University STEM Degrees*

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January 3, 2017

Abstract

This paper uses a change in enrollment requirements in Italian STEM majors to study the effects of university STEM education on the probability of becoming an inventor. Administrative data on education, occupations, and innovation activities of students who received a STEM degree thanks to the change in enrollment policy suggest that the propensity to innovate decreased among students with high pre-collegiate achievement, but increased among lower-achieving students. We show how these findings relate to heterogeneous sorting into more and less innovative occupations. In addition to affecting occupational choices, a university STEM education changed the type of innovation produced.

JEL Classification: I21, I25, I26, I28, J24, O30
Keywords: STEM, human capital, education policy, innovation, patents

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1 Introduction

The relationship between education and innovation has been the subject of intense scrutiny, due to its implication for economic growth and productivity (Jaffe, 1989; Aghion et al., 2009; Cantoni and Yuchtman, 2014; Andrews, 2016). Only recently, however, the growing availability of granular administrative data allowed researchers to describe on a large scale the individual drivers of innovation. Recent studies, for example, documented how inventors in several developed countries are more likely than average to have completed a university STEM (science, technology, engineering, and math) degree (Jung and Ejermo, 2014; Aghion et al., 2016). The next step in this line of research requires to identify the causal mechanisms through which scientific higher education affects the production of innovation. One important issue is to establish whether university STEM education has a direct effect of the propensity to innovate, beyond the fact that individuals who are inherently more inventive might choose to enroll in STEM majors. In addition, it would be critical to document how completing a university STEM degree changes occupational choices. If non-STEM industries value the skills acquired through a scientific education, many STEM graduates might end up in highly-paying jobs that do not focus on the production of innovation. In this case, the relationship between scientific education and innovation would depend critically on the characteristics of the local labor markets.

This paper uses a sharp change in the enrollment requirements of Italian STEM majors to study how university STEM education affects innovation. Until 1960, only the students who graduated from university-prep high schools (hereafter, academic students) could enroll in university STEM majors. Students in technical high schools for industry-sector professionals (industrial students) received a practical training in many STEM disciplines, but could not further their education at the university level. In 1961, industrial students were allowed to enroll in university STEM majors for the first time: between 1961 and 1964, universities could set enrollment quotas to control their entry; after 1965, any remaining restriction was lifted. Among the industrial students who completed high school after 1961, the probability of receiving a university STEM degree increased by more than 15 percentage points.

We leverage three types of administrative data on the population of 46,473 students who completed high school in Milan between 1958 and 1973. We use historical education data, which Bianchi (2016) collected directly from the archives of high schools and universities, to observe the pre-collegiate achievement and university career of these students. We also use a panel dataset provided by the Social Security Institute, which contains information on the employment histories of these individuals, to capture occupational choices. To measure the likelihood of producing innovation, we draw on information from all patents issued by

the Italian Patent Office (IPO) between 1968 and 2010, as well as from all international patents included in the European Patent Office's PATSTAT database. We then match the inventors listed in the patent data to school and employment records, using an individual fiscal code and the name of the employer. This process allows us to identify 869 individuals who patented at least once.

Our identification strategy exploits the fact that the change in enrollment requirements increased the probability of receiving a university STEM degree only among the industrial students who completed high school after 1961, but not among students from different high schools. Therefore, we can compare cross-cohort variations in innovation propensity between industrial and academic students, who could freely enroll in STEM majors before 1961, or between industrial students and graduates of other technical schools, who could not enroll in STEM majors even after 1961.[1] Because graduation rates in STEM majors increased more among industrial students with higher high school grades, we also estimate triple-difference regressions by comparing cross-cohort variations in innovation propensity between industrial and other students, and between levels of pre-collegiate achievement. In addition to this intent–to–treat analysis, we isolate the effect of the reform on the industrial students who actually received a STEM degree after 1961. To create a balanced sample, we use a nearest–neighbor algorithm to pair pre-reform industrial students to post-reform industrial students with a STEM degree on the basis of their pre-collegiate characteristics. We then compare these matched industrial students to academic students with a STEM degree.

We first analyze how acquiring a university STEM degree changed the probability of becoming an inventor. Among industrial students who scored in the top quartile of the high school exit exam and received a STEM degree, the propensity to innovate decreased between 43 and 58 percent. Industrial students with lower pre-collegiate achievement and a STEM degree, instead, became more likely to produce patents. To control for the quality of innovation, we repeat the analysis classifying as inventors only the 301 individuals who patented at least once in the US (35 percent of all inventors).[2] Data on US patents indicates that the probability to produce high-quality innovation did not decrease significantly among higher-achieving industrial students with a STEM degree. This finding suggests that the decrease observed using Italian and European patents might stems from individuals who would have not patented high-quality inventions in the US.

[1] The education policy might have induced some students, who would have otherwise chosen another school, to enroll in an industrial high school. In section 5.4, we perform several tests to address this concern. For example, we limit the analysis to early cohorts, who chose a high school before 1961. The available evidence suggests that a change in how students sorted into different high schools does not drive our findings.

[2] We treat the decision to patent in the US as a signal for inventions of above-average value, because Italian inventors have to incur significant additional expenses to file an application in the US.

We relate the previous heterogeneous effects on the propensity to innovate with changes in how industrial students with a STEM degree sorted into different occupations. The pre-reform cohorts of industrial students were mainly employed in manufacturing firms as high-skilled technicians, an occupation with a high probability of producing patents. After the reform, many higher-achieving industrial students with a STEM degree moved towards occupations with relatively low propensity to innovation, such as self–employed professionals and public servants. The occupation with the largest entry of higher-achieving industrial students, self-employed engineers, is characterized by both significant barriers to entry (a mandatory national exam) and high levels of income inequality, which might have deterred students with lower ability from entering. Lower-achieving industrial students with a STEM degree, instead, became employees in the private sector, either staying in manufacturing or moving to other innovative industries. They also became more likely to hold managerial roles, which are associated with a high propensity to innovate.

In addition to documenting how acquiring a STEM degree affected the selection into more or less innovative jobs, we study whether a scientific higher education had a direct impact on the type of innovation produced. Compared with industrial students, pre-reform academic students with a STEM degree were more likely to patent in important technological areas, such as medicine, chemistry, and IT. We label these areas as STEM–oriented fields of invention. We then show that post-reform industrial students with a STEM degree became more likely to patent in these STEM–oriented fields, suggesting that a university STEM degree made the innovation outcome of industrial and academic students more homogenous. This shift towards STEM–oriented fields does not seem to reflect any secular trend: post-reform industrial students who did not receive a STEM degree, for example, did not become more likely to patent in these areas.

This paper contributes to the vast literature on the returns to education. Previous research has highlighted how education leads to higher wages (Card, 1999, 2001; Meghir and Rivkin, 2011 for a review of this rich line of research), better health (Lleras-Muney, 2005; Silles, 2009; Cutler and Lleras-Muney, 2010; de Walque, 2010; Webbink, Martin and Visscher, 2010; Eide and Showalter, 2011), lower probability of incarceration and arrest (Lochner, 2004; Lochner and Moretti, 2004; Buonanno and Leonida, 2009; Cook and Kang, 2016), higher social capital (Dee, 2004; Milligan, Moretti and Oreopoulos, 2004; Wantchekon, Klasnja and Novta, 2015), and other non-monetary benefits (Grossman, 2006). This paper is one of the first to document how completing a university STEM degree, instead of a technical high school diploma, affects the propensity to innovate and the type of innovation. The results suggest that higher education has a more nuanced effect on innovation than on other outcomes. If innovation is tied to specific occupations and non-STEM sectors value

scientific skills, an increase in scientific education does not necessarily increase the propensity to innovate of marginal students.

To the best of our knowledge, there is only another paper that uses individual-level data to provide causal estimates on the relationship between education and innovation. Toivanen and Väänänen (2015) use the establishment of new technical colleges in Finland to instrument for the probability of getting a university engineering degree. Their IV estimates indicate a positive relationship between completed technical education and the propensity to patent in the US. This paper complements their analysis by showing the existence of heterogeneous effects between levels of pre-collegiate achievement, by relating changes in innovation propensity to sorting into different occupations, and by documenting effects on the fields of invention.

This paper also complements the recent, but growing literature that describes the observable characteristics of individual inventors. Jung and Ejermo (2014) draw on information on Swedish data to determine the existence of a significant gender gap. Depalo and Di Addario (2014) use data on Italian inventors to analyze how earnings change before and after the filing of a patent application. Aghion et al. (2016) analyze a dataset of Finnish inventors and find a positive correlation between parents' income and the probability of becoming an inventor. Using data on US inventors, Bell et al. (2016) emphasize how exposure to innovation during childhood is positively correlated with the propensity to innovate later in life. In this paper, we contribute to these findings by providing causal evidence on how education and occupations contribute to the likelihood of becoming an inventor.

The rest of the paper is organized as follow. Section 2 describes the change in the enrollment requirements in Italian STEM majors. Section 3 describes the data. Section 4 outlines the identification strategy. Section 5 shows the effects on the likelihood of becoming an inventor. Section 6 investigates changes in occupation. Section 7 documents the effects on the fields of invention. Section 8 concludes.

2 The Reform of the Admissions into University STEM Majors

In Italy, there are three main types of high schools: academic, technical, and professional schools. Academic schools provide a theoretical education in the humanities and the sciences. Technical schools combine theoretical and applied disciplines related to one field of study. These schools are categorized into different tracks, such as industry, commerce, and education. Technical students in the industrial-track, for example, study applied STEM disciplines, while students in the commercial-track study accounting and languages. Professional schools focus on short-term practical training for one specific occupation.

Until 1960, this three-tier high school system influenced admissions into Italian universities. At the top, the graduates of academic schools could choose any university major. In the middle, the graduates of technical schools could enroll only in business economics, statistics, and few other minor programs. Within this group, the students in the industrial-track were prevented from continuing their STEM studies at the postsecondary level and usually chose not to enroll in the university. At the bottom, the graduates of professional schools could not enroll in any university major.

As the Italian industrial sector expanded in the post-WWII period, the demand for highly skilled STEM workers increased significantly (figure A1). The growth in university STEM degrees, however, was constrained by the fact that only students of academic schools—amounting to 30.9 percent of all high school graduates in 1960—could enroll in university STEM majors. The first panel of figure A2 shows the number of students enrolled in the freshmen year of STEM majors in all Italian universities, computed as the share of all high school graduates. Between 1958 and 1960, the enrollment share in STEM majors was constant at 11 percent.

To increase the amount of STEM skills in the economy, a 1961 reform known as "*legge 685/61*" allowed industrial students to enroll in university STEM majors for the first time. The affected majors were engineering, mathematics, physics, natural sciences, biology, geology, and chemistry. Between 1961 and 1964, industrial students competed for a restricted number of available slots and were selected with an exam. Starting in 1965, industrial students were fully equated to academic students and stopped facing an enrollment cap. In 1969, a reform known as "*legge Codignola*" allowed all students to modify the previously rigid university curricula by choosing a higher number of elective courses.[3]

The 1961 reform was associated with a substantial enrollment increase in STEM majors. Between 1961 and 1964, the enrollment share in university STEM majors increased from 11.1 percent in 1960 to 12.9 percent in 1964 (panel A, figure A2; ISTAT data). When the remaining restrictions for industrial students were lifted in 1965, the enrollment share in university STEM majors increased to 18.6 percent. This large increase persisted at least until 1973. The second panel of figure A2 shows the number of industrial students enrolled in the freshman year of STEM majors, again computed as the share of all high school graduates. The enrollment share in STEM majors of industrial students was equal to 1.7 percent in 1963 and to 2 percent in 1964. In 1965, it increased dramatically to 6.8 percent and did not decrease throughout the period under consideration.

[3] The same "*legge Codignola*" granted all high school graduates access to any university major, regardless of the type of high school diploma. This part of the reform did not have any significant effect on the education choices of industrial students, as many of them kept enrolling in STEM programs.

3 Data

We analyze the effects of university STEM education on innovation by combining different types of administrative data on the students who completed high school in Milan between 1958 and 1973. Milan is an interesting setting for a study on innovative activities, due to its high propensity to innovation. According to the universe of patents issued by the Italian Patent Office between 1968 and 2010, 12.7 percent of the patents were granted to an assignee located in Milan, despite the fact that Milan hosts only 2.1 percent of the Italian population (2011 Census).

3.1 Education Data

Bianchi (2016) collected and digitized the high school registers of 46,473 students who received an academic or technical diploma in Milan between 1958 and 1973. In addition to key identifying variables such as full name, birthdate, and birthplace, the registers contain information about the student's performance in the high school exit exam (*maturità*). We standardize the high-school grades by school and cohort and use them as a measure of pre-collegiate achievement. Moreover, we can compute the average grade of each student's closest peers, because each cohort was divided in small classes of 20–30 students attending lectures together. We use the classmates' average score as a measure of pre-collegiate peer effects. From the registers, we also identify "home-schooled" students who graduated from the school without attending the regular school year. These students were either educated at home or enrolled in private schools not allowed to administer the final exam.

Bianchi (2016) also collected and digitized the student records kept by three universities in Milan: the Polytechnic University of Milan, the University of Milan, and the private Catholic University of the Sacred Hearth.[4] Collecting data exclusively from the universities in Milan does not lead to a biased sample, because almost all students from Milan chose a local university: 94.1 percent in 1956 and 93.5 percent in 1967, according to the Italian Bureau of Statistics (ISTAT). For each student, we know the major chosen, the year of enrollment, the grade received in each university course, and the final outcome (graduation, transfer, or dropout).

[4] Our sample does not include data from the private Bocconi University. Bocconi University is not relevant for the analysis, because it offered only a business economics major—accessible to technical students before 1961—, charged high tuition fees, and admitted only a limited number of students each year.

3.2 Occupation Data

Out of 46,473 students, 41,840 (90 percent) had a record in the database of the Italian Social Security Institute (INPS). INPS is a government agency that administers pensions and other forms of benefit mainly to employees in the private sector. The institute maintains an employer-employee panel database on all Italian workers, including self-employed and public employees. The information available for workers other than private employees, however, is limited to the pension fund to which they were contributing in a given year. Because the pension funds are tied to different jobs, we can categorize all workers in the sample into 40 occupations (table A1).

Most workers are employees in the private sector (64.4 percent), while public employees are 5.9 percent. The rest of the sample is represented by self-employed professionals, entrepreneurs, and other employees of private or public companies with special pension benefits (for example, the employees of the postal service).

For employees in the private sector, we have additional information on the industry, the position within the firm (apprentice, low/high blue collar, low/high white collar, or manager), and in some cases the compensation.

3.3 Patent Data

We measure the innovative activity of the individuals in the sample with data on the patents issued by the Italian Patent Office (IPO) between 1968 and 2010, and on the international patents included in the European Patent Office's PATSTAT database. The data distinguish between the assignees of a patent—the firms or individuals owning the intellectual property rights over the patented invention—and the inventors—the individuals who contributed to its development. This feature allows us to capture innovative activity, even when the individual develops a patent as an employee or consultant without retaining any property right.

We matched the list of high-school graduates to the list of inventors in different stages. Initially, we used the full name of the individuals to find 43,246 possible patent-individual matches. This first step ruled out the vast majority of irrelevant patents, but led to a large number of false positives. To improve the matching process, we employed three subsequent refinements. First, we exploited the fact that 7,796 matched patent-individual combinations issued after 1989 contained the fiscal code, which is a unique individual identifier for tax purposes. For these observations, we used the fiscal code of the students to find 496 correct and 7,300 incorrect matches. Second, we used the social security data to verify whether the employer of the alleged inventor matched the patent assignee in the year of the patent application. Thanks to the work histories provided by the social security institute, we were

able to verify 2,662 matches as correct and 27,642 as incorrect. Third, we hired several contractors to search additional information on the matched inventors, such as birthdate, birthplace, and education, on LinkedIn or company websites. To improve precision, we sent each entry (a patent-inventor combination) to multiple contractors and we personally checked all the data found online. Out of 880 patent-individual combinations for which we were able to find additional information, we were able to verify 663 of them as correct and 217 as incorrect. Out of the initial 43,246 matched patent-inventor combinations, we verified 35,159 entries and found 3,821 correct matches. In the main analysis, we dropped the 4,266 unverified patents from the sample, although the main results are robust to their inclusion (section 5.5).

3.4 Characteristics of Inventors

Out of 46,473 students, 869 inventors (1.9 percent of the sample) developed a total of 3,821 patents (Table 1). On average, one inventor is linked to 4 patents, but the distribution is heavily skewed to the right (median 2; 99th percentile 31). Relative to the rest of the sample, inventors are 22.9 percentage points more likely to be male and 0.7 years older. In addition, 64.1 percent of inventors received an industrial diploma, compared with 35.1 percent of non-inventors. As expected, inventors are positively selected in terms of academic abilities: they received a high school grade 0.26 standard deviations higher than the mean. Compared with the rest of the sample, inventors were more likely to attend university studies, especially in a STEM program, and were more likely to graduate. The retention rate in STEM majors is equal to 80 percent for inventors and 65.1 percent for the rest of the sample. In the labor market, 93.6 percent of inventors were employees in the private sector, compared with only 88.5 percent among non-inventors. Outside of the private sector, inventors were more prominent in research-oriented jobs, such as university professors and academic researchers (2.4 percent against 1.2 percent among non-inventors). Within the private sector, inventors were more likely to work in manufacturing (83.8 percent vs 52.1 percent) and in R&D (2.3 percent vs 0.9 percent). In addition, inventors were more likely to reach the top in the organizational structure of firms in the private sector. The share of managers is equal to 55.6 percent among inventors, but only 29.2 percent among non-inventors.

4 Identification

4.1 Industrial and Academic Students

In this specification, we draw a comparison between the innovative outcomes of industrial and academic students. Students with an academic diploma were not directly affected by the change in university access, since they could freely enroll in university STEM majors before and after 1961.[5] As a result, the policy significantly increased university STEM education only among the industrial students who completed high school after 1961. Relative to academic students, the graduation rate of industrial students in STEM majors increased by 4.0 percentage points between 1961 and 1964, by 17.2 percentage points between 1965 and 1968, and by 16.7 percentage points between 1969 and 1973 (table A2, panel A, column 1).[6] All increases are statistically and economically significant.

The differential increase in university STEM education occurred only among cohorts who finished high school after 1961, even though the reform granted every cohort of industrial students access to STEM degrees. The coefficients of the interaction between pre-reform cohort fixed effects, 1959 and 1960, and Industrial, a dummy variable equal to one for industrial students, are not statistically significant (table A2, panel A, column 2). Similarly, the coefficient of the interaction between a pre-reform linear trend and the variable Industrial is close to zero and not statistically significant (table A2, panel A, column 3). Figure 1 (panel A) shows that the differential change in university STEM education is the result of two separate effects: a large cross-cohort increase among industrial students, as well as a decrease among academic students. This decreasing pattern suggests that some academic students might have decided to avoid STEM majors after 1961, in favor of other programs still not accessible to industrial students (Bianchi, 2016). In section 4.5, we propose an alternative specification that takes this concern into account.

In the empirical analysis, we estimate the regression:

$$\text{Invention}_{it} = \alpha + \beta \text{Industrial}_i + \gamma_t + \sum_t \delta_t [\text{Industrial}_i \times \text{Post}_t] + \zeta X_{it} + u_{it} \qquad (1)$$

on a sample that comprises industrial and academic students. The unit of observation

[5] By granting access to university STEM majors, the 1961 reform significantly increased the option value associated with an industrial diploma. As a result, the selection of students into different types of high schools might have changed. In section 5.4, we perform several robustness checks to address this concern.

[6] Here and in the rest of the paper, the phrase "between 1961 and 1964" refers to the cohorts who completed high school between 1961 and 1964, "between 1965 and 1968" to the cohorts who completed high school between 1965 and 1968, and "between 1969 and 1973" to the cohorts who completed high school between 1969 and 1973.

is a student i, who completed high school in year t. The dependent variable Invention_{it} is a measure of innovative activity, such as a dummy variable equal to one for the individuals who developed at least one patent between 1968 and 2010, the number of developed patents, or the number of technological fields in which an individual invented. Post_t is a series of dummy variables that identify the cohorts who completed high school after the first policy implementation: Post 1961 is 1 for the students who completed high school between 1961 and 1964, Post 1965 is 1 for the students who completed high school between 1965 and 1968, and Post 1969 is 1 for the students who completed high school between 1969 and 1973. Industrial_i is a dummy that identifies industrial students. γ_t are cohort fixed effects, while X_{it} are student characteristics, such as gender, province of birth fixed effects, high school fixed effects, the average standardized score of the closest peers in high school, a dummy for home-schooled students, and a dummy for students who graduated high school on time at 19. Standard errors are clustered at the high school and cohort level.

We explore the existence of a common pre-trend in innovative activity between industrial and academic students by creating a new dataset in which each observation represents a different combination of year of high school graduation, high school class—defined as a small groups of 20–30 students attending lectures together—, and quartile of pre-collegiate achievement. We then test whether the number of inventors in industrial and academic classes followed a different trend before 1961. Panel A of table 2 shows that the coefficient of the interaction between a pre-reform trend and the dummy variable Industrial is not statistically different from zero (column 1). This finding does not change, if the linear trend is replaced by cohort fixed effects: the coefficients of Industrial x 1959 and Industrial x 1960 are small and not statistically significant (table 2, panel A, column 2). Similarly, there is no evidence of differential pre-reform trends, if we replace the inventor count with the number of patents developed by each observational unit (table 2, panel A, columns 3 and 4).

4.2 Industrial and Commercial Students

In this specification, we compare industrial students to graduates of commercial-track technical schools. Before 1961, commercial students could enroll in the same set of university majors that were available to industrial students. In 1961, however, they did not become eligible for STEM programs.[7] Relative to commercial students, the STEM graduation rate of industrial students increased by 3.7 percentage points between 1961 and 1964, by 13.1 percentage points between 1965 and 1968, and by 8.1 percentage points between 1969 and

[7] Commercial students could enroll in STEM majors only from 1969, when university admissions stopped depending on the type of high school diploma. Even after 1969, however, very few commercial students chose a STEM major.

1973 (table A2, panel B, column 1). In the empirical analysis, we then re-estimate regression (1) on a sample that includes solely industrial and commercial students. Panel B of table 2 indicates that the innovative activities of these two groups of students followed a common trend before the reform.

4.3 Higher– and Lower–Achieving Industrial Students

We then explore how university STEM education changed the innovative outcomes of industrial students with different pre-collegiate skills. Within each post-reform cohort, in fact, STEM graduation rates increased more among industrial students with higher pre-collegiate achievement (figure 1, panel C). Relative to industrial students with lower pre-collegiate achievement, the STEM graduation rates of industrial students who scored in the top quartile of the high school exit exam increased by 8.2 percentage points between 1961 and 1964, by 11.9 percentage points between 1965 and 1968, and by 9.6 percentage points between 1969 and 1973 (table A2, panel C, column 1). The inclusion of controls for pre-reform trends indicate that these increases do not precede the implementation of the first reform (table A2, panel C, columns 2 and 3).

We estimate the regression:

$$\text{Invention}_{it} = \alpha + \beta \text{Top}_i + \gamma_t + \sum_t \delta_t [\text{Top}_i \times \text{Post}_t] + \zeta X_{it} + u_{it}, \tag{2}$$

where Top_i is a dummy variable equal to 1 for industrial students in the top quartile of their high school grade distribution. This sample includes only students with an industrial diploma.

We investigate the existence of different pre-reform trends in the innovative outcomes of industrial students with varying pre-collegiate skills. The number of inventors among top and other industrial students were on the same path before 1961: the coefficient of the interaction between the variables Pre-reform trend and Top is close to zero and not statistically significant (table 2, panel C, column 1). These findings are robust to alternative specifications of both the pre-reform trend and the measure of innovative activity (table 2, panel C, columns 2 to 4).

4.4 Triple Differences

Equation 1 attributes any post-reform change in innovative activity among industrial students to the increase in STEM education. Omitted factors, however, might have differentially affected the propensity to innovate of industrial students who completed high school after

1961. Technological change, for example, might have differentially affected the propensity to innovate of younger industrial and academic students. We therefore compare the cross-cohort differential change in innovative activity of top and other industrial students to the differential change of top and other students with other high school diplomas. We estimate the regression:

$$\begin{aligned} \text{Invention}_{it} &= \alpha + \beta \text{Top}_i + \gamma_t + \sum_t \delta_t [\text{Top}_i \times \text{Post}_t] \\ &+ \sum_t \eta_t [\text{Industrial}_i \times \text{Post}_t] + \theta [\text{Industrial}_i \times \text{Top}_i] \\ &+ \sum_t \lambda_t [\text{Industrial}_i \times \text{Top}_i \times \text{Post}_t] + \zeta X_{it} + u_{it}, \end{aligned} \tag{3}$$

on two different samples, one with academic students as control and the other with commercial students. This difference-in-difference-in-differences specification allows us to control for time-varying omitted factors that differentially affected students with different diplomas, as well as students with varying pre-collegiate ability.

4.5 Matched Industrial and Academic Students

In addition to the previous intent-to-treat estimates, we intend to isolate the effect of university STEM education on the industrial students who actually received a STEM degree after 1961. The challenge in performing this analysis is that we do not directly observe the industrial students in the pre-reform cohorts who would have completed a STEM degree, had they graduated high school after 1961. To create a balanced pre-reform sample, we match post-reform industrial students with a STEM degree to pre-reform industrial students, using nearest–neighbor propensity score matching. We first limit the sample to male students, because female participation into high school increased over time. We then compute the propensity scores using the available pre-collegiate characteristics, such as high school fixed effects, the score in the exit exam, the average score of the high school's peers, a dummy for home–schooled students. We repeat this process for each quartile of pre-collegiate ability, choosing the calipers to match the observed STEM graduation rate after 1961.

The resulting sample of 1,719 industrial students has balanced characteristics before and after 1961 (table A3, panel A). All the observable characteristics used in the matching process are not statistically different between post-reform students with a STEM degree and matched pre-reform industrial students. Among higher-achieving students, for example, the average high school score is equal to 1.68 standard deviations among pre-reform matched students and to 1.75 standard deviations among post-reform students with a STEM degree.

The difference is small and not statistically significant. Moreover, also a variable not used to compute the propensity scores—a dummy that identifies students completing high school at the standard age of 19—is balanced between the two groups.

As a control group, we use academic students with a STEM degree. As a direct response to the entry of industrial students in STEM majors, however, some academic students might have turned to different university programs after 1961, changing the average characteristics of STEM students with an academic diploma. To address this concern, we select only the pre-reform academic students who were more likely to receive a STEM degree, had they completed high school after 1961. Using the same nearest–neighbor propensity score algorithm, we match post-reform academic students with a STEM degree to pre-reform academic students with a STEM degree. The result is a sample of 3,001 academic students with a STEM degree, whose characteristics are balanced across cohorts (table A3, panel B).

In the empirical analysis, we then re-estimate regression (1) on a sample that includes only matched industrial and academic students. Also for this specification, the data indicates that the innovative activity of these two groups of students followed a similar pre-reform path (table 2, panel D).

5 Effects on Innovation Propensity

This section describes the effects of increased university STEM education on innovation. Double– and triple–difference regressions reveal the existence of different effects between levels of pre-collegiate achievement.

5.1 Probability of Becoming an Inventor

5.1.1 Intent-to-Treat Analysis

We first estimate equation 1 using as the dependent variable an indicator for students that patented at least once between 1968 and 2010. There is no evidence of a differential change in the propensity to innovate between industrial and academic students who completed high school between 1961 and 1968 (Table 3, panel A, column 1). Among the cohorts who completed high school between 1969 and 1973, the propensity to innovate of industrial students decreased by 1.1 percentage points. The effect of increased STEM education, however, varied extensively across students with different pre-collegiate achievement.

The likelihood of becoming an inventor decreased for industrial students who scored in the top quartile of the high-school exit exam. Compared with top academic students, the propensity to innovate of top industrial students decreased by 0.02 percentage points between

1961 and 1964, by 3.2 percentage points between 1965 and 1968, and by 4.0 percentage points between 1969 and 1973. The last two coefficients are statistically significant at the 5 and 1 percent level, respectively. Considering that 7.4 percent of top industrial students became inventors before 1961, these effects imply that the propensity to innovate of top industrial students decreased by 43 to 54 percent. These results are robust to the inclusion of controls for pre-reform trends in the inventiveness of top industrial students (table 3, panel A, column 4). Panel A of figure 2 shows separately the cross-cohort change in the innovation propensity of top industrial and academic students. While the propensity to innovate of top academic students stayed fixed, the probability of becoming an inventor of top industrial students decreased significantly after 1965.[8]

Among lower-achieving industrial students, the propensity to innovate increased after the reform. Their probability of becoming an inventor increased by 1.2 percentage points between 1965 and 1968, and did not change significantly among other post-reform cohorts (table 3, panel A, columns 5 and 6).

The results are robust if we compare industrial and commercial students. Among students scoring in the top quartile of the grade distribution, the probability of becoming an inventor decreased by 4.2 percentage points between 1965 and 1968, and by 5.6 percentage points between 1969 and 1973 (table 3, panel B, column 3). Among lower-achieving students, the coefficients are close to zero, indicating small changes in innovation propensity (table 3, panel B, column 5).

We then estimate equation 2 by comparing industrial students in the top quartile of the grade distribution to industrial students with lower pre-collegiate achievement. The propensity to innovate of top industrial students decreased by 3.5 percentage points between 1965 and 1968, and by 3.6 percentage points between 1969 and 1973 (table A4, panel A, column 1). The estimates are robust to the inclusion of a linear pre-reform trend for top students, one for each ability quartile, one for each high school, and one for each combination of high school and ability quartile (table A4, panel A, columns 2-5).

We finally compare changes in innovative output between industrial and academic students, between levels of pre-collegiate achievement, and across cohorts of high school graduation. The likelihood of becoming an inventor among top industrial students decreased by 3.9 percentage points between 1965 and 1968, and by 3.3 percentage points between 1969 and 1973 (table A4, panel B, column 1). The findings of these triple differences are robust

[8] The lack of a significant decline between 1961 and 1964 could be due to the fact that these cohorts were still facing enrollment caps into STEM majors. In section B of the appendix, we explore a different hypothesis. Data from university transcripts show that students selected different electives exams after 1965. Different exam choices might have affected human capital accumulation and, in turn, innovation outcomes.

to the inclusion of different pre-reform trends (table A4, panel B, columns 2-5), as well as the use of commercial students as a control group (table A4, panel C).

5.1.2 Effect on the Industrial Students with a University STEM Degree

We isolate the effect of increased access into STEM majors on the industrial students who pursued a STEM degree after 1961 by matching pre-reform industrial students to post-reform industrial students with a STEM degree. In order to have a balanced control group, we also matched pre-reform academic students with a STEM degree to post-reform academic students with a STEM degree.

This analysis confirms that the effects of scientific education on innovation are heterogeneous across levels of pre-collegiate achievement. Among industrial students scoring in the top quartile of the high school exit exam and receiving a STEM degree, the probability of becoming an inventor decreased by 0.4 percentage points between 1961 and 1964, by 6.8 percentage points between 1965 and 1968, and by 6.3 percentage points between 1969 and 1973 (table 3, panel C, column 3). These findings suggest that the innovation propensity decreased by 53 to 58 percent after 1965, relative to the pre-reform baseline.

Among industrial students scoring in the bottom three quartiles of the high school exit exam and receiving a STEM degree, the probability of becoming an inventor increased by 6.6 percentage points between 1961 and 1964, by 7.9 percentage points between 1965 and 1968, and by 5.3 percentage points between 1969 and 1973 (table 3, panel C, column 5). All three coefficients are statistically different from zero and robust to the inclusion of a linear pre-reform trend (table 3, panel C, column 6).[9]

5.2 Number of Patents and Technological Fields

We estimate equations 1 with two alternative measures of innovative output: the number of developed patents, and the number of different fields of invention. Industrial students who received a STEM degree after 1961 and scored in the top quartile of pre-collegiate achievement did not develop fewer patents after 1961 (the coefficients are negative after 1965, but not statistically significant), but were active inventors in fewer technological areas (table A5, panel C).[10] Top industrial students produced patents in 0.16 fewer fields between

[9] This increase in the incidence of inventors did not show as clearly in the previous intent-to-treat analysis, because the number of STEM graduates is relatively low in the bottom three quartiles of pre-collegiate achievement. Moreover, this finding does not originate from the fact that the matching process selected fewer inventors among the pre-reform cohorts. The share of inventors before 1961, in fact, is equal to 5.6 percent in the matched sample and only to 3.5 percent in the full sample.

[10] The results of the intent-to-treat analysis are in panel A (vs. academic students) and B (vs. commercial students) of table A5. The triple–difference specifications are in the appendix table A6.

1965 and 1968, and in 0.15 fewer fields between 1969 and 1973 (table A5, panel C, column 2). The magnitude of these coefficients indicate a 60 to 64 percent decrease in the number of active research fields.[11]

Industrial students scoring in the bottom three quartiles of pre-collegiate achievement developed more patents after 1961 and became active inventors in more technological areas. Lower-achieving industrial students with a STEM degree produced 1.3 more patents between 1961 and 1964, 0.6 more patents between 1965 and 1968, and 0.4 more patents between 1969 and 1973 (table A5, panel C, column 5). Similarly, they became active inventors in 0.19 more fields between 1961 and 1964, in 0.20 more fields between 1965 and 1968, and in 0.15 more fields between 1969 and 1973 (table A5, panel C, column 6). These findings are robust to the estimation of negative binomial regressions (table A5, panel C, columns 7 and 8).

We isolate variations in the productivity of inventors by estimating the same regressions on the smaller sample of students who developed at least one patent (table A7). Although most estimates are not precise, the number of active research fields increased significantly after 1961 among lower-achieving industrial inventors with a STEM degree (table A7, panel C, columns 6 and 8).

5.3 Controlling for Patent Quality

The patent count is an imperfect measure of innovation because patents can vary in their innovative content (Griliches, 1990). To control for patent quality, Trajtenberg (1990) suggests using the number of forward citations, because a common requirement in patent applications is to include references to previous related inventions. Citations, however, are not available in the Italian patent data. To address this issue, we matched the 46,473 individuals in our sample with inventors in the NBER US Patent Citation Data File (Hall, Jaffe and Trajtenberg, 2001), following the same procedure described in section 3.3. Out of 869 total inventors in our sample, 301 individuals patented at least once in the United States. We consider these 301 individuals as inventors of higher-quality (or higher-valuation) patents, because for an Italian inventor patenting is more expensive in the US than in Italy.[12]

We then repeat our analysis on the probability of developing at least one patent issued by the US Patent Office (table A12). The intent-to-treat analysis (panels A and B) is consistent with the main findings in table 3: the decrease in innovation propensity is larger

[11] Negative binomial estimates suggest that top industrial students produced patents in 0.11 fewer fields between 1965 and 1968, and in 0.12 fewer fields between 1969 and 1973, although the coefficients are not statistically different from zero (table A5, panel C, column 4).

[12] Although the direct fees charged by the two patent offices are comparable (a minimum of $70 in the US and €50 in Italy), an Italian inventor who aspires to patent in the the US will need a professional English translation of the patent documents and most likely the help of a local patent attorney.

among higher-achieving industrial students. If we focus on the individuals who received a STEM degree after 1961 (panel C), the data reveal different effects for higher– and lower–achieving students. Among industrial students scoring in the top quartile of the pre-collegiate distribution and receiving a STEM degree after 1961, there is not a significant change in innovation propensity. This finding is robust to two different dependent variables: a dummy for inventors of US patents (table A12, panel C, column 3), and the citation-weighted number of developed US patents (table A12, panel C, column 4). The fact that the decrease in innovation that we observe in the Italian patent data is not present in the US patent data suggests that this decrease is driven by individuals who would have ended up producing lower-valuation inventions not covered by US patents.

Among lower-achieving industrial students with a STEM degree, instead, there is a significant increase in innovation propensity. The probability of developing at least one US patent increased by 4.8 percentage points between 1961 and 1964, by 5.3 percentage points between 1965 and 1968, and by 3.7 percentage points between 1969 and 1973 (table A12, panel C, column 5). The coefficients are statistically significant at the 10, 5, and 10 percent level, respectively.

5.4 Controlling for Entry into Industrial High Schools

The reform might have changed selection into different high schools, drawing into industrial schools students who were interested in pursuing a university STEM degree. Here, we present several tests that address this concern.

We first estimate equation 2 using only data from either academic students (A9, panel A) or commercial students (A9, panel B). In both cases, the analysis indicates that the probability of becoming an inventor did not change after 1961 between academic or commercial students with higher and lower pre-collegiate achievement. The coefficients of the interaction between post-reform cohort dummies and Top_i are all close to zero and not statistically significant.[13] These findings rule out the hypothesis that the most or least inventive students switched to industrial schools after the reforms, because the average probability of becoming an inventor did not change among students attending other high schools.

Second, we estimate equation 1 on a smaller sample of students who completed high school before 1966. These cohorts, in fact, enrolled in high school before the implementation of the first policy (1961) and could not easily transfer to other types of schools after 1961.[14] Among

[13] The findings are robust to the choice of different dependent variables, such as the number of developed patents or the number of different areas of innovation (table A9, columns 3 to 6).

[14] Strong anticipation effects were not likely, because the reform was swiftly implemented by a short-lived government. During this time period, the instability of coalition governments created uncertainty on the

high-achieving industrial students, the intent-to-treat analysis confirms that the decrease in innovation started before 1966. Compared with academic students, the probability of becoming an inventor of top industrial students decreased by 0.9 percentage points between 1961 and 1964, and by 4.8 percentage points in 1965 (table A10, panel A, column 2). If we focus on the top industrial students who received a STEM degree, the data indicates that the probability of becoming an inventor decreased by 4.52 percentage points between 1961 and 1964, and by 4.7 percentage points in 1965 (table A10, panel C, column 2). These coefficients, however, are not precisely estimated. Among industrial students who scored in the bottom three quartiles of pre-collegiate achievement, the increase in the innovation propensity is statistically significant before 1966. In panel C, for example, the data indicates that lower-achieving industrial students with a STEM degree became more likely to innovate by 8.1 percentage points between 1961 and 1964, and by 14.7 percentage points in 1965, relative to pre-reform cohorts and academic students with a STEM degree (table A10, panel C, column 6). The results are robust to the use of commercial students as a control group (table A10, panel B, column 2).

We also estimate equation 1 using weights that keep the average observable characteristics of the sample constant across pre- and post-reform cohorts (DiNardo, Fortin and Lemieux, 1996). These weighted OLS estimators confirm the existence of a decrease in innovation propensity among top industrial students. Compared with academic students, the probability of becoming an inventor of top industrial students decreased by 0.6 percentage points between 1961 and 1964, by 3.9 percentage points between 1965 and 1968, and by 4.3 percentage points between 1969 and 1973 (table A10, panel A, column 3). Among industrial students scoring in the bottom three quartiles of the pre-collegiate achievement, instead, the share of inventors increased by 1.3 percentage points between 1965 and 1968. The coefficients are close to the baseline OLS estimates in table 3.[15]

5.5 Controlling for Unverified Student–Inventor Matches

In the previous analysis, we dropped all the student-inventor matches that we could not verify through the fiscal code, the social security data, or online searches (4,266 unverified patents, 9.9 percent of all matches). In this section, we explore whether the main findings change, when the unverified inventors are included in the sample. We first exploit the verified

introduction of new policies. Between 1958 and 1970, 13 different governments lasted on average only 9.5 months in power.

[15] In tables A10 and A11, we include two additional tests. First, we estimate a probit regression, instead of a linear probability model. Second, we identify as inventors only the individuals who developed at least one patent between 29 and 56 years old, the age range that we observe for all cohorts in the sample. These robustness checks confirm the main findings.

student-inventor matches to assess how the observable characteristics of patents and inventors correlate to the probability of a correct match. We then use these estimates to predict the probability of being a correct match for the unverified student-inventor combinations. In table A13, we document that the baseline findings are robust to the inclusion of unverified inventors.

When we include unverified inventors with a probability of being a correct match above 50 percent, for example, the total number of inventors increases to 901 individuals. The estimates still indicate that the inventor share of top industrial students decreased by 2.7 percentage points between 1965 and 1968, and by 3.9 percentage points between 1969 and 1973 (table A13, panel A, column 5). These coefficients are significant at 10 and 1 percent level, respectively. Even when we include all unverified inventors (2,399 total inventors) in the sample, the intent-to-treat estimates indicate a significant decrease in the innovation propensity of top industrial students who completed high school after 1969 (table A13, panel A, column 8). These findings are robust across all specifications (table A13, panels B to E).

6 Selection into Occupations

Why did the propensity to innovate decrease only among higher-achieving students after 1961? To provide an explanation, this section explores how industrial students sorted into different occupations after 1961. After 1961, higher-achieving industrial students with a STEM degree moved to occupations with relatively low levels of innovation, such as self-employed engineers. Most lower-achieving industrial students with STEM degrees, instead, remained employees in the private sector - similar to what industrial students in the pre-reform cohorts did - but they became more likely to work in industries that produce more patents. They also became more likely to be employed as managers, who are more often listed as inventors in patent applications.

6.1 Changes Across Occupations

We document how sorting into occupations changed after 1961 among industrial students with a STEM degreein Panel A of figure 3. The blue bars represent the difference between the share of post-reform industrial students with a STEM degree and the share of pre-reform industrial students in each occupation. At the top of the graph, there are the occupations that experienced the largest entry of industrial students with a STEM degree. Relative to the pre-reform cohorts, industrial students with a STEM degree became more likely to work as self-employed engineers (+4.3 percentage points), other self-employed professionals (+3 percentage points), public employees for the central government (+2.6 percentage points)

or local governments (+1.9 percentage points). At the bottom of the graph, there are the occupations that experienced the largest exit of industrial students with a STEM degree. The industrial students who received a STEM degree after 1961 became less likely to be employed in the private sector (-5.3 percentage points), or to work as artisans (-4.8 percentage points), entrepreneurs (-3.1 percentage points), and self-employed surveyors (-1.2 percentage points). The red bars denote the innovation propensity of different jobs, measured as the share of inventors out of the total number of workers employed in each occupation. The graph reveals that the industrial students with a STEM degree abandoned occupations with a relatively high propensity to produce patents: for example, 1.6 percent of private employees developed at least one patent during their career, 1.2 percent of artisans, 0.7 percent of entrepreneurs, and 1.9 percent of industrial technicians. The inflow of industrial students with STEM degree, however, was mostly concentrated among occupations with lower propensity to innovate: only 0.6 percent of self-employed engineers produced patents, 0.6 percent of other self-employed professionals, 0 percent of public employees in the central government, and 0.1 percent of local public employees. Although a university STEM degree granted them access to highly innovative jobs, entry into these occupations was limited. For example, the share of industrial students employed as certified biologists, an innovative occupation that requires a STEM degree, increased by only 0.3 percentage points.

Panel B of figure 3 shows how sorting into occupations by industrial students without a STEM degree changed after 1961. This graph presents two main features. First, the magnitude of the occupational changes is much smaller, compared with the figure in panel A. The decrease in the share of private employees after 1961, for example, is equal to only 3.4 percentage points, instead of 5.3 percentage points. Second, industrial students without a STEM degree moved to different occupations after 1961, compared with students with a STEM degree. Among the occupations that experienced the largest entry, there are entrepreneurs, local public employees, workers in the entertainment sector, and health workers. These stark differences between panel A and B of figure 3 confirm that the occupational sorting of industrial students with STEM degrees is not the result of secular changes in the Italian economy, but is likely a direct consequence of the expanded access into STEM majors.

In the rest of this section, we test the previous findings in a regression format. We also explore the existence of heterogeneous effects across levels of pre-collegiate achievement. We estimate:

$$\text{Occupation}_{ity} = \alpha + \beta \text{Industrial}_i + \gamma_t + \sum_t \delta_t [\text{Industrial}_i \times \text{Post}_t] + \zeta X_{it} + \phi_y + u_{ity} \quad (4)$$

The unit of observation is a student i, who completed high school in year t, in the calendar year y. The dependent variable Occupation_{ity} denote one of three different variables: Engineers_{ity} is one for self-employed engineers; S-e prof._{ity} is one for self-employed professionals, including engineers; Top occ._{ity} is equal to one for the four occupations (top decile) with the highest share of inventors: chemists, biologists, pharmacists, and academics; and Researchers_{ity} is one for researchers at institutions of higher education. ϕ_y are calendar year fixed effects. The rest of the variables have already been introduced in the previous analysis. To streamline the discussion, for the remainder of the paper we will focus on two different specifications: first, an intent-to-treat analysis, in which we compare all industrial and academic students; second, an analysis focused on students with a STEM degree, using the matching process described in section 4.5.

Industrial students in the top quartile of pre-collegiate achievement became more likely to become self-employed engineers after 1961, a profession with a relatively low level of innovation propensity. More specifically, the probability of working as a self-employed engineer increased by 1.2 percentage points between 1961 and 1968, and by 1.3 percentage points between 1969 and 1973. (table 4, panel A, column 1).[16] The effects are larger, if we consider other forms of self-employed professionals (table 4, panel A, column 2). There is no evidence, however, that higher-achieving industrial students disproportionally entered into highly-innovative occupations, in spite of an increase in the number of STEM degrees after 1961. The probability of working in a highly-innovative occupation decreased by 3.1 percentage points between 1961 and 1964, by 5.95 percentage points between 1965 and 1968, and by 2.6 percentage points between 1969 and 1973 (table 4, panel A, column 3). Similarly, the probability of working in a research-based occupation decreased by 3.1 percentage points between 1961 and 1964, by 5.4 percentage points between 1965 and 1968, and by 2.5 percentage points between 1969 and 1973 (table 4, panel A, column 4).[17]

For industrial students who scored in the bottom three quartiles of pre-collegiate achievement, the data does not indicate any significant increase in the probability of working as a self-employed engineer. Especially after 1965, the estimated effects are a precisely estimated zero (table 4, panel A, column 5). There is also additional evidence that the lower-achieving students did not move towards highly innovative occupations. The probability of working in the most innovative jobs, for example, decreased by 0.6 percentage points between 1961 and 1964, by 1.6 percentage points between 1965 and 1968, and by 1.1 percentage points between

[16] As in the previous analysis, the treatment effects refer to cohorts of high school graduation, not to calendar years. The phrase "between 1969 and 1973", for example, identifies the average occupational change for the cohorts who completed high school between 1969 and 1973, considering all calendar years in the dataset.

[17] In these occupations, the estimated decrease in employment share is the result of a slight increase among industrial students that is outpaced by a larger rise among academic students.

1969 and 1973 (table 4, panel A, column 7). Compared with the coefficients estimated for higher-achieving students, these last estimates have a much smaller magnitude, suggesting that movements across occupations after 1961 were less common among students with lower pre-collegiate achievement.

The results are robust if we re-estimate equation (4) on the smaller sample of students with a STEM degree (table 4, panel B). Higher-achieving industrial students who received a STEM degree after 1961 became self-employed engineers or other professionals, occupations with low levels of innovation propensity. The employment share in these occupations increased by 6.4 percentage points between 1961 and 1964, by 3.5 percentage points between 1965 and 1968, and by 2.4 percentage points between 1969 and 1973 (table 4, panel B, column 2). The first two coefficients are statistically significant at the 1 and 5 percent level, respectively. Higher-achieving industrial students, however, did not disproportionately enter into highly-innovative occupations, compared with higher-achieving academic students (table 4, panel B, columns 3 and 4). Lower-achieving students with a STEM degree, instead, were less likely to move across occupations. Their likelihood to work as self-employed engineers did not change significantly between 1961 and 1968, and decreased by 2.2 percentage points between 1969 and 1973 (table 4, panel B, column 5). Their employment share in innovative occupations increased between 1961 and 1964, but did not change significantly between 1965 and 1973 (table 4, panel B, columns 7 and 8).

These findings are in line with the observed changes in innovation propensity. Higher-achieving students moved to jobs with high barriers to entry, mainly self-employed engineers, that did not produce many patents. Lower-achieving students, instead, were less likely to move towards occupations with higher barriers to entry than the private sector, because of their lower human capital or the worse signal provided by their grades. In the next section, we will explore potential mechanisms through which their propensity to innovate might have increased within the private sector.

6.2 Changes Within the Private Sector

By leveraging additional information that is available only for employees in the private sector, we analyze how industrial students with STEM degrees sorted into different industries (Italian ATECO 91 categorization). In panel A of figure A4, the blue bars measure the change in employment share within each industry between post-reform industrial students with STEM degrees and pre-reform industrial students. The red bars, instead, measure the share of inventors in each industry. After 1961, many industrial students with STEM degrees left manufacturing (-9.9 percentage points), the third industry by share of inventors.

The employment share increased in industries with low levels of innovation, such as software distribution (+4.3 percentage points) and education (+3.7 percentage points), as well as in more innovative sectors, such as the extractive industry (+1.4 percentage points) and R&D (+0.9 percentage points). Panel B of figure A4 shows how industrial students without a STEM degree sorted into different industries after 1961. In this case, there is no entry in the highly-innovative industries. The employment share in R&D, for example, increased by only 0.2 percentage points.

In table A14, we show estimates of equation 4, using five different dependent variables: $\text{Manufacturing}_{ity}$ is a dummy that identifies manufacturing industries; $\text{R\&D}_{ity}$ is equal to one for research–intensive industries; two variables identify public services (Education_{ity} and $\text{Other public}_{ity}$); Top pay is a dummy for the five industries with the highest average salaries for workers with STEM degrees (Energy, Food/Hospitality, Transportation/Communications, Finance/Banking, and International organizations). The intent-to-treat estimates in panel A indicate that lower-achieving industrial students became more likely to work in R&D, one of the most innovative industries, after 1965. Panel B of table A14 describes industry changes for the industrial students with a STEM degree. The higher-achieving industrial students left manufacturing (table A14, panel B, column 2), but did not move into R&D (table A14, panel B, column 1). Their employment share, instead, increased in industries producing public services, such as education (table A14, panel B, columns 3 and 4).[18] In addition, their likelihood of being employed in a high-paying industry increased by 8.3 percentage points between 1965 and 1968, and by 8.6 percentage points between 1969 and 1973 (table A14, panel B, column 5).

Lower-achieving industrial students, instead, either stayed in manufacturing or moved to other innovative sectors. Their probability of working in R&D increased by 7.7 percentage points between 1961 and 1964, by 5.3 percentage points between 1965 and 1968, and by 3.8 percentage points between 1969 and 1973 (table A14, panel B, column 5).

In addition to analyzing changes across industries, we can study how the roles held by industrial students changed after 1961. In the Italian labor system, there are seven formal positions within firms in the private sector that carry increasing responsibilities: apprentices, blue–collar, high–skilled blue–collar ("*intermedi*"), white–collar, high–skilled white collar ("*quadri*"), and managers. Higher–ranked positions also have a higher propensity to innovate. Managers, for example, have an inventor share equal to 2.1 percent, compared with only 0.1 percent among blue–collar workers. Panel A of figure A5 shows how industrial students with a STEM degree sorted into different positions. The share working in blue–collar jobs decreased by 15.2 percentage points, while the share working in higher–ranked positions

[18] Their employment share increased also in industries producing private services, such as banking.

increased: 8.5 percentage points for high–skilled white collar, 3.5 percentage points for managers, and 3.3 percentage points for white–collar. Panel B of figure A5 shows how industrial students without a STEM degree moved across different positions. In this case, the shifts are smaller in magnitude and are not directed towards higher–ranked positions.

Wethen estimate equation 4using two alternative dependent variables: Top pos.$_{ity}$ is equal to one for high–skilled white–collar and managers; and Managers.$_{ity}$ is equal to one for managers only. Panel A shows intent-to-treat estimates, computed by comparing all industrial and academic students across subsequent cohorts. Overall, both higher- and lower-achieving industrial students became more likely to work as managers after 1961, but the effect is larger and more robust among lower-achieving students. The likelihood of higher-achieving students to hold a top position increased by 5.9 percentage points between 1965 and 1968, and by 5.4 percentage points between 1969 and 1973 (table A15, panel A, column 1). If we include industry fixed effects, the coefficients become smaller and insignificant, suggesting that the previous increase was realized mainly through movements across industries (table A15, panel A, column 3). Among lower–achieving students, instead, the probability of holding a top position increased by 6.50 percentage points between 1965 and 1968 without the inclusion of industry fixed effects (table A15, panel A, column 5), and by 6.6 percentage points with the inclusion of industry fixed effects (table A15, panel A, column 7). In panel B, we show that the general findings are robust, if we estimate equation 4 on the smaller sample of students who received a STEM degree after 1961. The increase in the rate of employment in the highest–ranked positions is larger among lower–achieving industrial students. The inclusion of industry fixed effects reduces the estimates, although in this specification the coefficients remain statistically significant for both levels of pre-collegiate achievement.

7 Effects on the type of innovation

In the previous analysis, we showed how pursuing a university STEM degree was associated with opposite effects on the propensity to innovate of students with different levels of pre-collegiate achievement. We then related changes in the probability of developing patents to occupational sorting. In this section, we study whether a university STEM education had a direct impact on the innovative activities of industrial students by leveraging information on the field of invention from patent applications. Each granted patent, in fact, is assigned to a class that identifies the technological area to which the invention belongs. Following the International Patent Classification (IPC), we divide the matched patents into 10 major fields: human necessities, medicine (class A61), industrial operations, chemistry, textiles,

constructions, mechanical engineering, physics, electricity, and IT (classes H03, H04, G06, and G11).

Industrial and academic students patented in different technological areas before 1961. In the first panel of figure 4, we plot the distribution of inventors in pre-reform cohorts across different technological areas, separately for industrial students (blue bars) and academic students with a STEM degree (orange bars): 24.7 percent of inventors with an academic diploma patented in the field of chemistry, compared with only 13.1 percent of inventors with an industrial diploma. Similarly, academic students with STEM degrees were more likely to patent in medicine (9.3 percent vs 7.1 percent), textiles (3.1 percent vs 1.2 percent), constructions (6.2 percent vs 2.4 percent), and IT (4.1 percent vs 3.6 percent). The industrial students who pursued a STEM degree after 1961 began patenting more in the same fields in which academic students with a STEM degree were more common before 1961 (figure 4, panel B). The share of inventors with an industrial diploma and a STEM degree increased by 7.1 percentage points in chemistry, and by 8.2 percentage points in medicine. In industrial operations, in which industrial students were more likely to patent before the reform, the share of industrial inventors with a STEM degree decreased by 5.1 percentage points. The industrial students who did not receive a STEM degree after 1961 exhibit a different pattern (figure 4, panel C). Their likelihood to patent did not increase in chemistry and medicine, but increased by 1.1 percentage points in industrial operations. This last graph suggests that more patenting in fields like chemistry and medicine by industrial students who pursued a STEM degree after 1961 does not reflect secular changes in technology, but is likely driven by access to university STEM education.

To further analyze changes in the type of innovation, we re-estimate equation 1 on the sample of individuals who patented at least once. In these regressions, the dependent variable STEM field$_{it}$ is equal to one, if an inventor patented at least once in a STEM–oriented technological areas. We define STEM–oriented fields as the areas in which academic students with STEM degree were more likely to patent before 1961. The likelihood of industrial students to patent in medicine, chemistry, or IT increased by 26.4 percentage points between 1965 and 1968, and by 21.5 percentage points between 1969 and 1973 (table 5, panel A, column 1). The coefficients imply a 58 to 72 percent increase, relative to the baseline. The results are robust to the use of a less restrictive definition of STEM–oriented fields, which includes all five areas with a higher share of academic inventors before 1961 (medicine, chemistry, IT, constructions, textiles). In this case, the probability of industrial students to patent in STEM fields increased by 26.09 percentage points between 1965 and 1968, and by 28.10 percentage points between 1969 and 1973 (table 5, panel A, column 1). If we repeat the analysis separately on higher- (columns 3 and 4) and lower-achieving students (columns

5 and 6), the coefficients remain positive, but are less precisely estimated.[19]

If we focus on the smaller sample of students who attained a STEM degree, the estimates indicate a large increase in the probability of innovating in STEM–oriented fields after 1961. The probability of patenting in a STEM–oriented field increase by 69.9 percentage points between 1965 and 1968, and by 46.7 percentage points between 1969 and 1973 (table 5, panel B, column 1).

8 Discussion and conclusions

In this paper, we study how graduating in a STEM major affects the probability of becoming an inventor. We find heterogeneous effects between levels of pre-collegiate achievement. Students who scored in the top quartile of their high school class became less likely to produce patents, once they gained access to STEM majors. Lower-achieving students, instead, experienced an increase in their likelihood of becoming inventors. We then relate these findings to information on work histories, which were provided by the Italian Social Security Institute (INPS). To the best of our knowledge, this paper is the first to document how investments in human capital affect innovation propensity through changes in occupational sorting. Higher–achieving students moved to desirable jobs with low levels of innovation, such as self–employed engineers. Most lower-achieving students, instead, did not choose self-employment or the public sector. As employees in the private sector, however, they moved to more innovative industries. Moreover, they became more likely to hold managerial roles, which are more commonly associated with the production of patents. A STEM degree allowed these students, who would have attained only a high school diploma in the absence of the policy, to break the ceiling that previously blocked their career progression within firms in the private sector. In addition to affecting how students sorted into occupations, graduating in a STEM major had an effect on the type of innovation produced. Conditional on becoming inventors, the students who received a STEM degree became more likely to patent in STEM–oriented fields, such as medicine and chemistry.

These findings depict a complex relationship between education and innovation, which is shaped by the characteristics of the local labor market. Higher–achieving students moved towards self-employment and public services, usually choosing occupations with significant barriers to entry. To work as a self-employed engineer, for example, candidates must possess a STEM degree and pass an additional national exam. Similarly, public servants are chosen through lengthy examinations, in which academic achievements are usually part of the

[19] This increase in the standard errors is likely due to the small size of the two samples: only 241 higher-achieving and 577 lower-achieving inventors.

selection criteria. These requirements can keep lower-achieving candidates out, making these professions more attractive to individuals with higher ability. Moreover, the high variance of returns in self–employment might deter lower-achieving students, who might find advantageous that firms in the private sector cannot adjust wages below thresholds agreed with the unions. [20] In addition to the previous hypotheses, the salience of the final high school ("*voto di maturità*") and university ("*voto di laurea*") scores in the Italian labor market might also explain why many lower-achieving students did not become freelance engineers. Self–employment, in fact, might force a worker to repeatedly establish new business relationships, making it harder to overcome the weak signal provided by poor academic achievements.

While the results are consistent with the characteristics of the local labor market, we believe that the mechanisms discussed in this paper apply beyond the Italian setting. In many developed countries, STEM skills are now sought after by industries that do not focus on the production of patents, like finance. According to the US Census Bureau, for example, 74 percent of STEM graduates are not employed in a STEM occupation (Census Bureau, 2014). In this context, any effort to encourage innovation by increasing the number of STEM graduates would need to take into account how these students sort into non-STEM jobs. Our findings, which suggest that the relationship between education and innovation depends crucially on the characteristics of the labor market, are consistent with this scenario, even though Italy in the 1960s and 1970s was different from any modern Western country. Moreover, the Italian reform might be more directly informative about any large–scale plan to increase scientific skills in the developing world (for example, the Science Education Programme by UNESCO). The Italian government, in fact, intended to increase the number of university-educated workers to sustain industrial growth, a problem currently faced by many developing countries. The Italian experience suggests that, even in a less developed economy, the features of the local labor market might influence the relationship between scientific education and innovation.

References

Aghion, Philippe, Akcigit Ufuk, Ari Hyytinen, and Otto Toivanen. 2016. "Living the "American Dream" in Finland: The Social Mobility of Inventors."

[20] Unfortunately, we don't observe the labor income of self-employed engineers directly in our data. Nationally representative data from the Bank of Italy's Survey of Household Income and Wealth (SHIW)—available here—indicate that the labor income variance of self-employed engineers is substantial higher than that of STEM workers in manufacturing. For instance, the yearly standard deviation in labor income is 7,096 euro for self-employed engineers, and 3,956 euro for STEM workers in manufacturing.

Aghion, Philippe, Leah Platt Boustan, Caroline M. Hoxby, and Jérôme Vandenbussche. 2009. "Causal Impact of Education on Economic Growth: Evidence from U.S."

Andrews, Michael. 2016. "The Causal Effect of Colleges on Local Patenting: Evidence from the Formative Years of U.S. Higher Education, 1870-1940." working paper.

Bell, Alex, Raj Chetty, Xavier Jaravel, Neviana Petkova, and John Van Reenen. 2016. "The Lifecycle of Inventors."

Bianchi, Nicola. 2016. "The Indirect Effects of Educational Expansions: Evidence from a Large Enrollment Increase in STEM Majors." working paper.

Buonanno, Paolo, and Leone Leonida. 2009. "Non-market effects of education on crime: Evidence from Italian regions." *Economics of Education Review*, 28(1): 11–17.

Cantoni, Davide, and Noam Yuchtman. 2014. "Medieval Universities, Legal Institutions, and the Commercial Revolution." *Quarterly Journal of Economics*, 129(2): 823–887.

Card, David. 1999. "The Causal Effect of Education on Earnings." In *Handbook of Labor Economics*. Vol. 5, , ed. Orley Ashenfelter and David Card, 1801–1863. New York:North-Holland.

Card, David. 2001. "Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems." *Econometrica*, 69(5): 1127–1160.

Census Bureau. 2014. "Majority of STEM College Graduates Do Not Work in STEM Occupations." Census Bureau Report CB14-130.

Cook, Philip J., and Songman Kang. 2016. "Birthdays, schooling, and crime: Regression-discontinuity analysis of school performance, delinquency, dropout, and crime initiation." *American Economic Journal: Applied Economics*, 8(1): 33–57.

Cutler, David M., and Adriana Lleras-Muney. 2010. "Understanding differences in health behaviors by education." *Journal of Health Economics*, 29(1): 1–28.

Dee, Thomas S. 2004. "Are there civic returns to education?" *Journal of Public Economics*, 88(9-10): 1697–1720.

Depalo, Domenico, and Sabrina Di Addario. 2014. "Inventors' Returns to Patents." Unpublished manuscript.

de Walque, Damien. 2010. "Education, Information, and Smoking Decisions. Evidence from Smoking Histories, 1940-2000." *Journal of Human Resources*, 45(3): 682–717.

DiNardo, John, Nicole M. Fortin, and Thomas Lemieux. 1996. "Labor Market Institutions and The Distribution of Wages, 1973 - 1992: A Semiparametric Approach." *Econometrica*, 64(5): 1001 – 1044.

Eide, Eric R., and Mark H. Showalter. 2011. "Estimating the relation between health and education: What do we know and what do we need to know?" *Economics of Education Review*, 30(5): 778–791.

Griliches, Zvi. 1990. "Patent Statistics as Economic Indicators: A Survey." *Journal of Economic Literature*, 28(4): 1661–1707.

Grossman, Michael. 2006. "Education and Nonmarket Outcomes." In *Handbook of the Economics of Education*. Vol. 1, Chapter 10, 577–633.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg. 2001. "The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools." NBER Working Paper 8498.

Istituto Nazionale di Statistica. n.d.. *Annuario Statistico dell'Istruzione Italiana. Anni*

1955-1975. Roma.

Jaffe, Adam. 1989. "Real Effects of Academic Research." *American Economic Review*, 79(5): 957–70.

Jung, Taehyun, and Olof Ejermo. 2014. "Demographic patterns and trends in patenting: Gender, age, and education of inventors." *Technological Forecasting and Social Change*, 86: 110–124.

Lleras-Muney, Adriana. 2005. "The relationship between education and adult mortality in the United States." *Review of Economic Studies*, 72(January): 189–221.

Lochner, Lance J. 2004. "Education, work, and crime: A human capital approach." *International Economic Review*, 45(3): 811–843.

Lochner, Lance J., and Enrico Moretti. 2004. "The effect of education on crime: Evidence from prison inmates, arrests, and self-reports." *American Economic Review*, 94(1): 155–189.

Meghir, Costas, and Steven Rivkin. 2011. "Econometric Methods for Research in Education." In *Handbook of the Economics of Education*. Vol. 3. 1 ed., 1–87. Elsevier Ltd.

Milligan, Kevin, Enrico Moretti, and Philip Oreopoulos. 2004. "Does education improve citizenship? Evidence from the United States and the United Kingdom." *Journal of Public Economics*, 88(9-10): 1667–1695.

Silles, Mary A. 2009. "The causal effect of education on health: Evidence from the United Kingdom." *Economics of Education Review*, 28(1): 122–128.

Toivanen, Otto, and Lotta Väänänen. 2015. "Education and Invention." *Review of Economics and Statistics*, forthcoming.

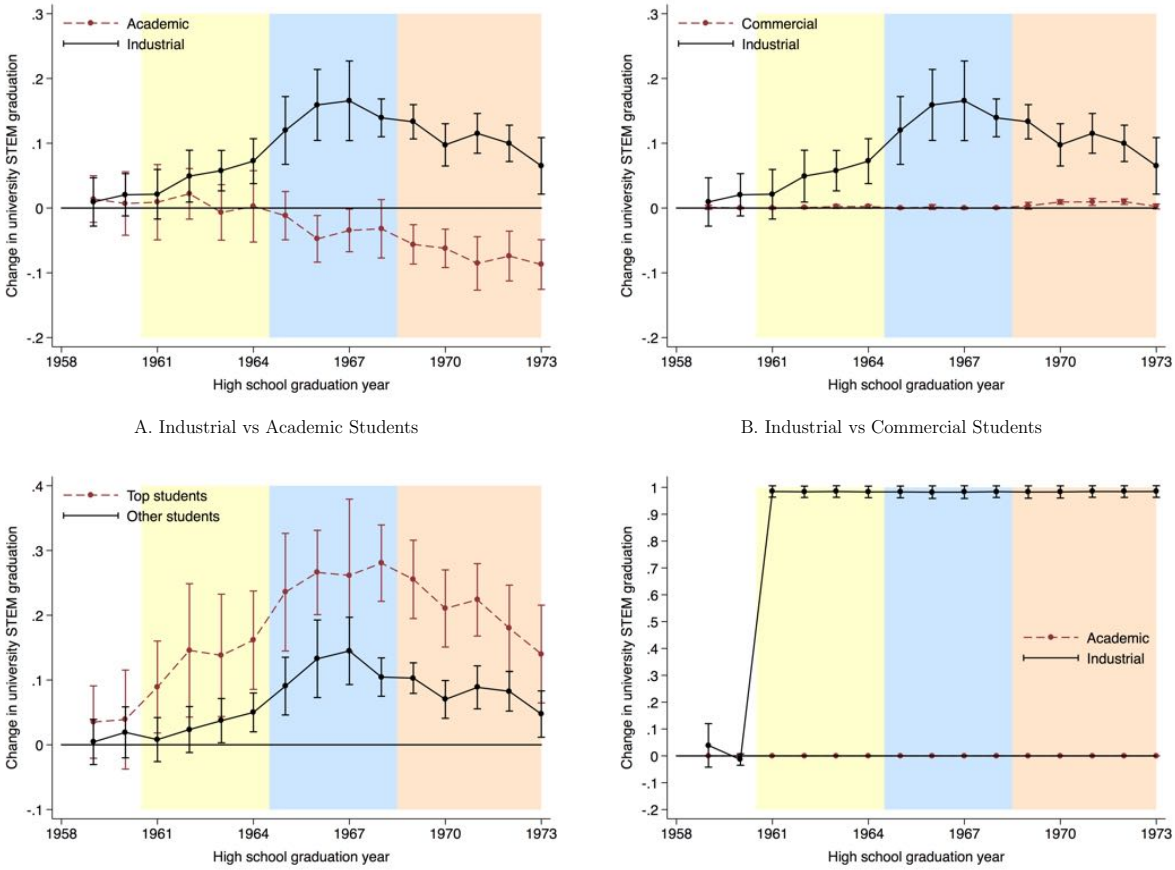
Trajtenberg, Manuel. 1990. "A penny for your quotes: patent citations and the value of innovations." *The RAND Journal of Economics*, 21(1): 172–187.

Wantchekon, Leonard, Marko Klasnja, and Natalija Novta. 2015. "Education and Human Capital Externalities: Evidence from Colonial Benin." *The Quarterly Journal of Economics*, 130(2): 703–757.

Webbink, Dinand, Nicholas G. Martin, and Peter M. Visscher. 2010. "Does education reduce the probability of being overweight?" *Journal of Health Economics*, 29(1): 29–38.

Figures and Tables

Figure 1: Differential Increase in Graduation Rates from University STEM Majors



A. Industrial vs Academic Students

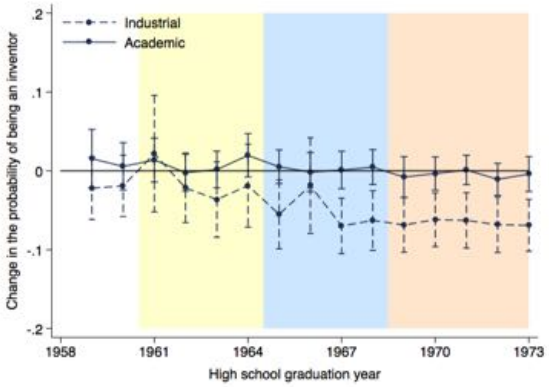
B. Industrial vs Commercial Students

C. Top vs Other Industrial Students

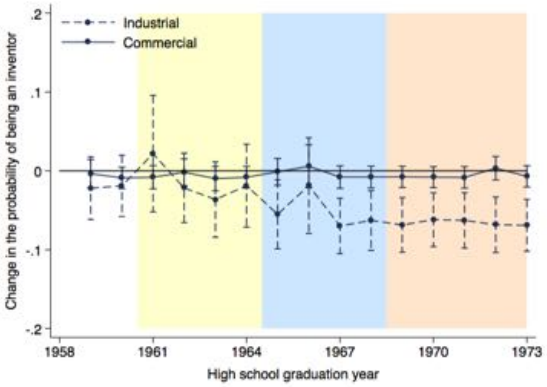
D. Matched Industrial vs Academic Students

Notes: This graph shows the change (and 95 percent CIs) in the graduation rate from university STEM majors for different groups of students. Industrial students could enroll in STEM majors for the first time in 1961. In the yellow-shaded area, industrial students faced enrollment caps in STEM majors. In the blue-shaded area, industrial students could freely enroll in STEM majors. In the orange-shaded area, students had more freedom in the choice of the university curriculum. Academic students (panel A) had access to STEM majors throughout the time period under analysis. Commercial students (panel B) could not enroll in university STEM majors until 1969, when any high school diploma started granting access to all majors. Top industrial students (panel C) received a final high school grade in the top quartile of their school distribution. Panel D uses propensity score matching to identify a subgroup of academic and industrial students in the pre-period with the same observable characteristics of students in the post-period with a STEM degree. The regressions control for gender, province of birth fixed effects, high school fixed effects, the high school standardized score, the average standardized score of the closest peers in high school, a dummy for home-schooled students, and a dummy for students who graduated high school at 19 (and likely never repeated a grade). Standard errors clustered by school and cohort.

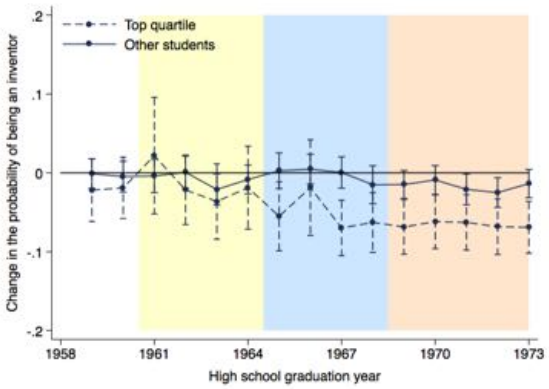
Figure 2: Cross-Cohort Change in Inventor Share



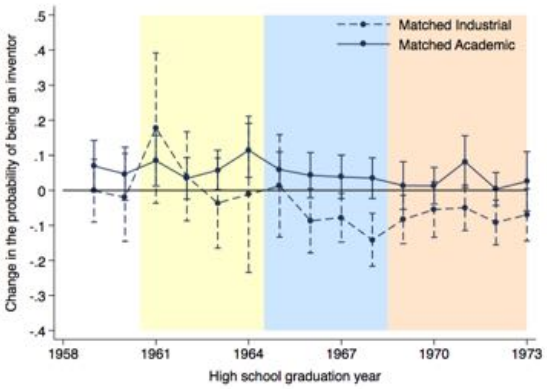
A. Top Industrial vs Top Academic Students



B. Top Industrial vs Top Commercial Students



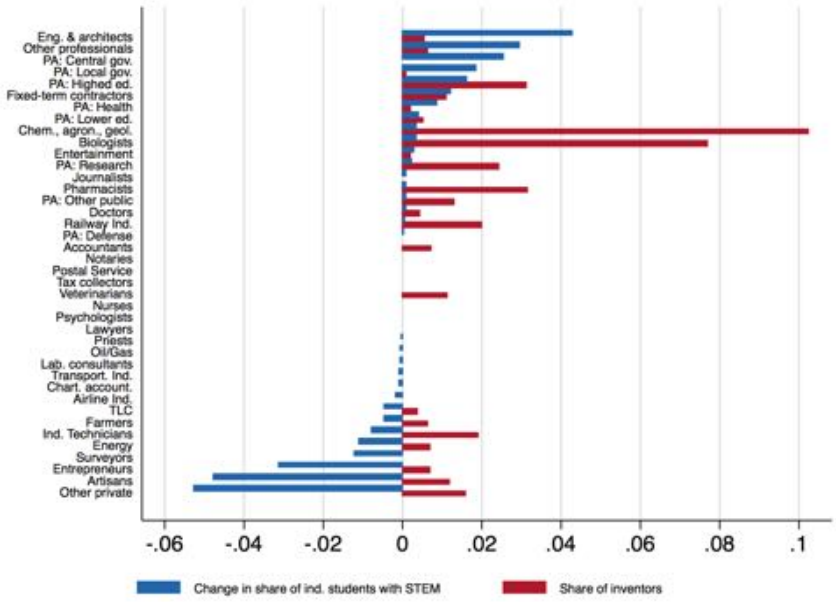
C. Top vs Other Industrial Students



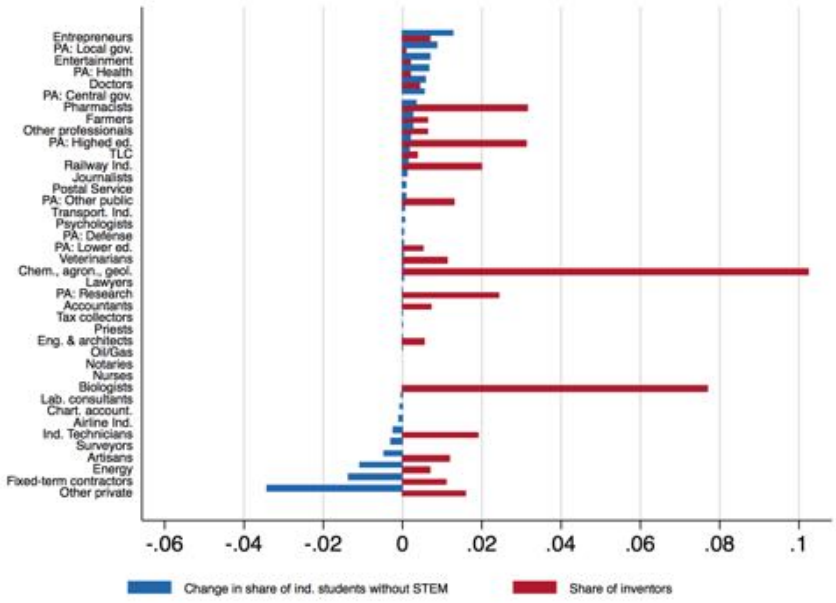
D. Top Matched Industrial vs Academic Students

Notes: This graph shows the change (and 95 percent CIs) in the inventor share across subsequent cohorts for different groups of students. Industrial students could enroll in STEM majors for the first time in 1961. In the yellow-shaded area, industrial students faced enrollment caps in STEM majors. In the blue-shaded area, industrial students could freely enroll in STEM majors. In the orange-shaded area, students had more freedom in the choice of the university curriculum. Academic students (panel A) had access to STEM majors throughout the time period under analysis. Commercial students (panel B) could not enroll in university STEM majors until 1969, when any high school diploma started granting access to all majors. Top industrial students (panel C) received a final high school grade in the top quartile of their school distribution. Panel D uses propensity score matching to identify a subgroup of top academic and industrial students in the pre-period with the same observable characteristics of top students in the post-period with a STEM degree. The regressions control for gender, province of birth fixed effects, high school fixed effects, the high school standardized score, the average standardized score of the closest peers in high school, a dummy for home-schooled students, and a dummy for students who graduated high school at 19 (and likely never repeated a grade). Standard errors clustered by school and cohort.

Figure 3: Distribution of Inventors across Occupations



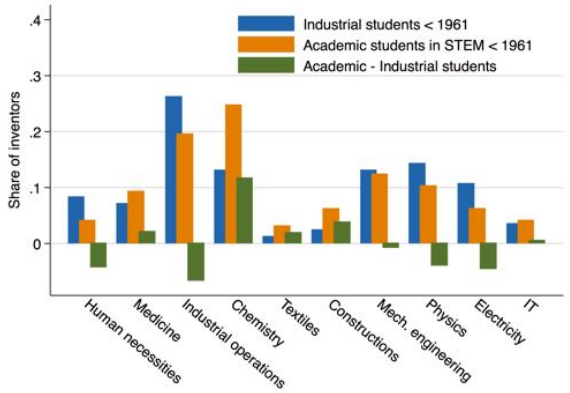
A. Change for Industrial Students with a STEM Degree



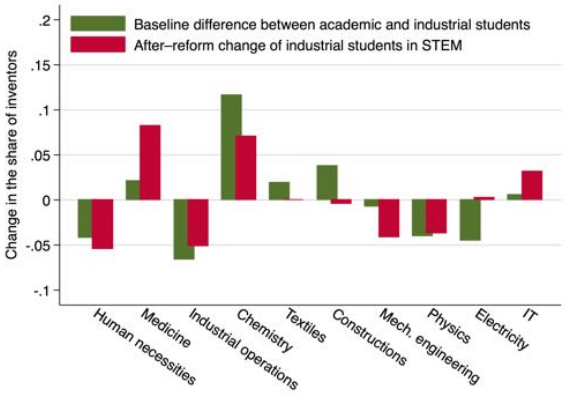
B. Change for Industrial Students without a STEM Degree

Notes: These graphs show how the distribution of industrial students across different occupations changed among the cohorts who completed high school after 1961. Panel A shows how the distribution of industrial students who received a STEM degree after 1961 changed, relative to the pre-reform distribution. Panel B shows how the distribution of industrial students who did not receive a STEM degree after 1961 changed, relative to the pre-reform distribution. Share of inventors measures the percentage of inventors in each occupation, pooling all available years of patent data (1968-2010).

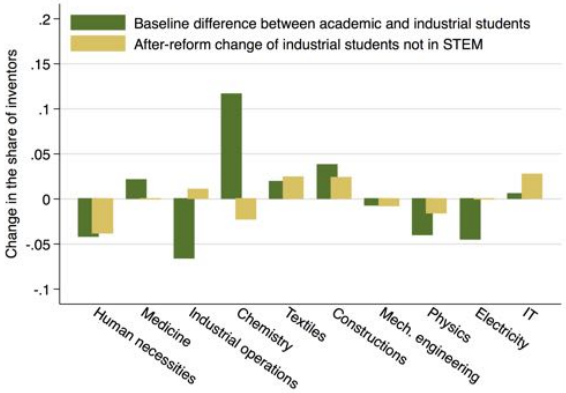
Figure 4: Distribution of inventors across technological fields



A. Academic students with STEM degree vs Industrial students before 1961



B. After–reform change for industrial students with STEM degree



C. After–reform change for industrial students without STEM degree

Notes: These graphs show the distribution of inventors across different technological fields. Panel A shows the pre-reform distribution of academic students with a STEM degree and industrial students across technological fields. Panel B shows the post-reform change for industrial students who received a STEM degree after 1961. Panel C shows the post-reform change for industrial students who did not receive a STEM degree after 1961.

Table 1: Summary Statistics

	Inventors	Non-inventors	Difference
	(1)	(2)	(3)
Observations	869	45,604	
Male	0.962	0.721	0.229***
Birth year	1945.44	1946.29	0.771**
Patent data			
Number of patents	4.010	-	-
Number of technological fields	1.478	-	-
Education data			
Academic diploma	0.320	0.409	-0.044
Industrial diploma	0.641	0.351	0.233***
HS exit score	0.256	-0.005	0.246***
Score of HS peers	0.009	0.000	0.020
Home schooled	0.043	0.102	-0.046***
Non-repeater	0.959	0.930	0.019*
Enrolled	0.653	0.568	0.133***
Enrolled in a STEM major	0.490	0.192	0.304***
University degree	0.479	0.343	0.162***
University STEM degree	0.392	0.125	0.265***
Labor market outcomes			
Private employees	0.936	0.885	0.051***
Researchers	0.026	0.015	0.011**
Manufacturing*	0.838	0.521	0.317***
R&D*	0.023	0.009	0.014**
Managers*	0.556	0.292	0.264***
Highly skilled white collar*	0.209	0.154	0.055***

Notes: The sample is composed of 46,473 individuals who completed high school in Milan between 1958 and 1973. The high school score is the grade received in the high school final exam. It is standardized by cohort and high school. The HS peers are groups of 20-30 students within a cohort attending all lectures together. Home-schooled students took only the final exam in the school, even though they did not attend there the regular school year. They could be enrolled in private schools that could not administer the final exam or they could be home–educated. Non-repeater were 19 years old at the time of the final exam (the standard age of high school graduation). STEM majors are engineering, physics, mathematics, biology, geology, natural science, and chemistry. Researchers are employees of institutions of higher education. (*) These variables are available only for employees in the private sector and only starting in 1983.
Sources: High school archives; university transcripts; patents issued by the Italian patent office between 1968 and 2010; international patents collected by the European Patent Office in the PATSTAT database; social security data.

Table 2: Pre-Reform Trends in Innovative Activity

	Inventor count (1)	Inventor count (2)	Patent num. (3)	Patent num. (4)
Panel A: Industrial vs academic students				
Industrial x Pre-reform trend	-0.0109		-0.0589	
	(0.0455)		(0.0913)	
Industrial x 1959		-0.0007		-0.0587
		(0.0768)		(0.2005)
Industrial x 1960		-0.0222		-0.1178
		(0.0911)		(0.1829)
Panel B: Industrial vs commercial students				
Industrial x Pre-reform trend	0.0018		-0.0371	
	(0.0420)		(0.0874)	
Industrial x 1959		-0.0041		-0.0425
		(0.0704)		(0.1898)
Industrial x 1960		0.0050		-0.0752
		(0.0843)		(0.1751)
Panel C: Top vs other industrial students				
Top x Pre-reform trend	0.0357		0.0715	
	(0.1043)		(0.1754)	
Top x 1959		0.0048		0.1195
		(0.1849)		(0.3924)
Top x 1960		0.0715		0.1429
		(0.2092)		(0.3521)
Panel D: Matched, Industrial vs academic students				
Industrial x Pre-reform trend	-0.0001		-0.2119	
	(0.0800)		(0.1784)	
Industrial x 1959		0.1135		-0.0508
		(0.1763)		(0.5284)
Industrial x 1960		-0.0169		-0.4704
		(0.1607)		(0.3488)

Notes: The dependent variables are the average number of inventors (columns 1 and 2) and the average number of patents by unit of observation. (columns 3 and 4). Industrial is a dummy that equals 1 for students who attended an industrial high school. Top is a dummy that equals 1 for the students who ranked in the top quartile of their school's grade distribution. For the double differences, the single interactions of the variables are not reported. For the triple differences, the single and double interactions of the variables are not reported. The unit of observation is a pre-reform cohort of high school graduation (between 1958 and 1960)–high school class (small groups of 20-30 students)–quartile of pre-collegiate achievement combination. The number of observations is equal to 756 in panel A, 582 in panel B, and 275 in panel C, and 316 in panel D. Standard errors clustered by high school class and quartile of ability in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3: Probability of Becoming an Inventor, Industrial vs Other Students

	Inventor (1)	Inventor (2)	Inventor (3)	Inventor (4)	Inventor (5)	Inventor (6)
Panel A: Industrial vs academic students						
Industrial x Post 1961	-0.0004	-0.0033	-0.0002	-0.0066	-0.0011	-0.0041
	(0.0066)	(0.0091)	(0.0172)	(0.0213)	(0.0059)	(0.0110)
Industrial x Post 1965	0.0035	0.0005	-0.0317**	-0.0381*	0.0122**	0.0093
	(0.0059)	(0.0088)	(0.0144)	(0.0193)	(0.0061)	(0.0111)
Industrial x Post 1969	-0.0109**	-0.0138*	-0.0403***	-0.0467***	-0.0028	-0.0058
	(0.0052)	(0.0083)	(0.0120)	(0.0177)	(0.0053)	(0.0108)
Industrial x Pre-reform trend		-0.0029		-0.0060		-0.0029
		(0.0060)		(0.0128)		(0.0069)
Panel B: Industrial vs commercial students						
Industrial x Post 1961	-0.0044	-0.0058	-0.0039	-0.0057	-0.0060	-0.0082
	(0.0057)	(0.0073)	(0.0147)	(0.0188)	(0.0047)	(0.0083)
Industrial x Post 1965	-0.0081	-0.0095	-0.0420***	-0.0438**	-0.0007	-0.0030
	(0.0050)	(0.0067)	(0.0127)	(0.0176)	(0.0050)	(0.0085)
Industrial x Post 1969	-0.0217***	-0.0231***	-0.0559***	-0.0577***	-0.0133***	-0.0155*
	(0.0042)	(0.0061)	(0.0097)	(0.0158)	(0.0040)	(0.0079)
Industrial x Pre-reform trend		-0.0013		-0.0017		-0.0020
		(0.0047)		(0.0105)		(0.0052)
Panel C: Matched, Industrial vs academic students						
Industrial x Post 1961	0.0412	0.0440	-0.0044	-0.0219	0.0664*	0.1120**
	(0.0377)	(0.0449)	(0.0501)	(0.0554)	(0.0387)	(0.0512)
Industrial x Post 1965	0.0225	0.0253	-0.0679**	-0.0854**	0.0795***	0.1252***
	(0.0248)	(0.0341)	(0.0334)	(0.0410)	(0.0292)	(0.0448)
Industrial x Post 1969	-0.0001	0.0027	-0.0629**	-0.0806**	0.0532*	0.0991**
	(0.0215)	(0.0319)	(0.0296)	(0.0378)	(0.0272)	(0.0435)
Industrial x Pre-reform trend		0.0030		-0.0209		0.0408
		(0.0262)		(0.0339)		(0.0283)
Sample	All	All	Top	Top	Other	Other
Pre-reform inventor share (panel A-B)	0.0427	0.0427	0.0740	0.0740	0.0346	0.0346
Pre-reform inventor share (panel C)	0.0897	0.0897	0.1176	0.1176	0.0563	0.0563
Observations (panel A)	35,479	35,479	7,662	7,662	27,817	27,817
Observations (panel B)	27,497	27,497	5,865	5,865	21,632	21,632
Observations (panel C)	4,718	4,718	1,807	1,807	2,911	2,911

Notes. This table shows the effect of the promotion of STEM education on the probability of becoming an inventor by comparing industrial to academic students (panel A), industrial to commercial students (panel B), and matched industrial to academic students (panel C). The matching selects students in the pre-period, who share the same observable characteristics of the individuals with a STEM degree in the post-period. The dependent variable, Inventor, is a dummy that equals one for students who patented at least once from 1968 to 2010. Post 1961 is 1 for the cohorts who graduated between 1961 and 1964, Post 1965 is 1 for the cohorts who graduated between 1965 and 1968, and Post 1969 is 1 for the cohorts who graduated between 1969 and 1973. Pre-reform trend is a linear trend for pre-reform cohorts. Columns 3 and 4 restrict the sample to students who ranked in the top quartile of their school's grade distribution. Columns 5 and 6 restrict the sample to students who are not in the top ability quartile. The regressions also include cohort fixed effects, gender, province of birth fixed effects, high school fixed effects, the high school standardized score, the average standardized score of the closest peers in high school, a dummy for home-schooled students, and a dummy for students who graduated high school at 19 (and likely never repeated a grade). Standard errors clustered by high school and cohort in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Changes in Occupation

	Engineers (1)	S-e prof. (2)	Top occ. (3)	Researchers (4)	Engineers (5)	S-e prof. (6)	Top occ. (7)	Researchers (8)
Panel A: Industrial vs academic students								
Industrial x Post 1961	0.0120**	0.0150*	-0.0308***	-0.0314***	-0.0050**	-0.0079**	-0.0057**	-0.0062**
	(0.0058)	(0.0080)	(0.0092)	(0.0093)	(0.0023)	(0.0034)	(0.0029)	(0.0024)
Industrial x Post 1965	0.0120**	0.0200**	-0.0595***	-0.0539***	-0.0007	-0.0028	-0.0155***	-0.0170***
	(0.0061)	(0.0082)	(0.0110)	(0.0109)	(0.0023)	(0.0033)	(0.0036)	(0.0032)
Industrial x Post 1969	0.0128**	0.0212***	-0.0259***	-0.0248***	-0.0006	0.0002	-0.0113***	-0.0076***
	(0.0061)	(0.0079)	(0.0072)	(0.0070)	(0.0024)	(0.0033)	(0.0030)	(0.0021)
Panel B: Matched, Industrial vs academic students								
Industrial x Post 1961	0.0442***	0.0638***	0.0056	-0.0119	0.0019	-0.0020	0.0528*	0.0497
	(0.0160)	(0.0196)	(0.0258)	(0.0256)	(0.0109)	(0.0167)	(0.0317)	(0.0314)
Industrial x Post 1965	0.0222*	0.0352**	-0.0052	0.0003	-0.0054	-0.0093	-0.0021	-0.0023
	(0.0120)	(0.0153)	(0.0228)	(0.0232)	(0.0081)	(0.0121)	(0.0120)	(0.0120)
Industrial x Post 1969	0.0052	0.0240	-0.0453***	-0.0410**	-0.0221**	-0.0226*	0.0055	0.0033
	(0.0132)	(0.0150)	(0.0149)	(0.0160)	(0.0099)	(0.0129)	(0.0085)	(0.0077)
Sample	Top	Top	Top	Top	Other	Other	Other	Other
Pre-reform dep. var. (panel A)	0.000	0.009	0.000	0.000	0.002	0.008	0.000	0.000
Pre-reform dep. var. (panel B)	0.000	0.004	0.000	0.000	0.000	0.007	0.000	0.000
Observations (Panel A)	234,961	234,961	234,961	234,961	802,657	802,657	802,657	802,657
Observations (Panel B)	59,122	59,122	59,122	59,122	93,272	93,272	93,272	93,272

Notes. This table shows the effect of the promotion of STEM education on the occupation choice. Dependent variables: Engineers is 1 for freelance professional engineers, S-E Prof. is 1 for self-employed professionals (including freelance engineers), Top Occ. is a dummy for the top 10 percent occupations in terms of share of inventors (self-employed biologists, self-employed chemists, pharmacists, and public employees of institutions of higher education), Researchers is 1 for research-intensive occupations in institutions of higher education. Post 1961 is 1 for the cohorts who graduated between 1961 and 1964, Post 1965 is 1 for the cohorts who graduated between 1965 and 1968, and Post 1969 is 1 for the cohorts who graduated between 1969 and 1973. Columns 1 to 4 restrict the sample to students who ranked in the top quartile of their school's grade distribution. Columns 5 to 8 restrict the sample to students who ranked in the bottom three quartiles of their school's grade distribution. The regressions include cohort and calendar year fixed effects, gender, province of birth fixed effects, high school fixed effects, the HS score, the average standardized score of the closest peers in high school, a dummy for home-schooled students, and a dummy for students who graduated high school at 19. Standard errors clustered by student in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Type of Innovation

	STEM field (1)	STEM field (2)	STEM field (3)	STEM field (4)	STEM field (5)	STEM field (6)
	Panel A: Industrial vs academic students					
Industrial x Post 1961	0.1485	0.1406	0.2948	0.2230	0.0145	0.0199
	(0.0930)	(0.0925)	(0.1994)	(0.2361)	(0.1376)	(0.1285)
Industrial x Post 1965	0.2637***	0.2609***	0.2874	0.1870	0.2369*	0.2871**
	(0.0864)	(0.0869)	(0.2192)	(0.2451)	(0.1229)	(0.1243)
Industrial x Post 1969	0.2145**	0.2810***	0.3979*	0.3228	0.0989	0.1926*
	(0.0988)	(0.0926)	(0.2366)	(0.2405)	(0.1196)	(0.1137)
	Panel B: Matched, Industrial vs academic students					
Industrial x Post 1961	0.1557	0.0890	0.3657	0.1666	-0.0423	0.0582
	(0.1571)	(0.1482)	(0.3738)	(0.4129)	(0.2963)	(0.2863)
Industrial x Post 1965	0.6997***	0.6773***	0.5784	0.3130	0.7473***	0.7417***
	(0.1627)	(0.1563)	(0.3855)	(0.3810)	(0.2208)	(0.2019)
Industrial x Post 1969	0.4672***	0.5070***	0.7695**	0.6805*	0.4265*	0.4613**
	(0.1728)	(0.1665)	(0.3584)	(0.3660)	(0.2179)	(0.2021)
Sample	All	All	Top	Top	Other	Other
STEM fields	Three	Five	Three	Five	Three	Five
Pre-reform dep. var. (panel A)	0.3676	0.3971	0.2800	0.3200	0.4186	0.4419
Pre-reform dep. var. (panel B)	0.2857	0.2857	0.3000	0.3000	0.2500	0.2500
Observations (panel A)	818	818	241	241	577	577
Observations (panel B)	310	310	118	118	192	192

Notes. This table shows changes in the type of innovation. Columns 1 to 3 show estimates using the whole sample, columns 4 to 6 use only students in the top quartile of the ability distribution, and columns 7 to 9 use only the students in the bottom three quartiles of the ability distribution. The dependent variable is a dummy that equals one if the individual patented at least once in a STEM field. In Columns 1, 3, and 5, the STEM fields are medicine, chemistry, and IT. In Columns 2, 4, and 6, the STEM fields are medicine, chemistry, textiles, constructions, and IT. Standard errors clustered by high school and cohort in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix - Not For Publication

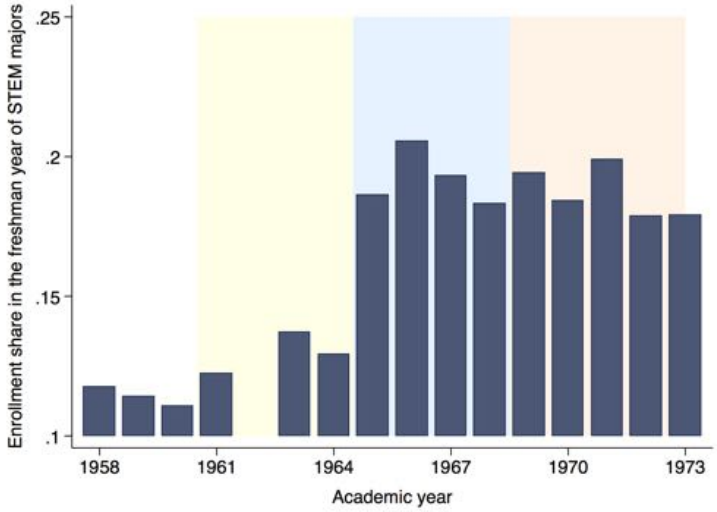
A Additional Figures and Tables

Figure A1: Selected Headlines about Lack of STEM Skills

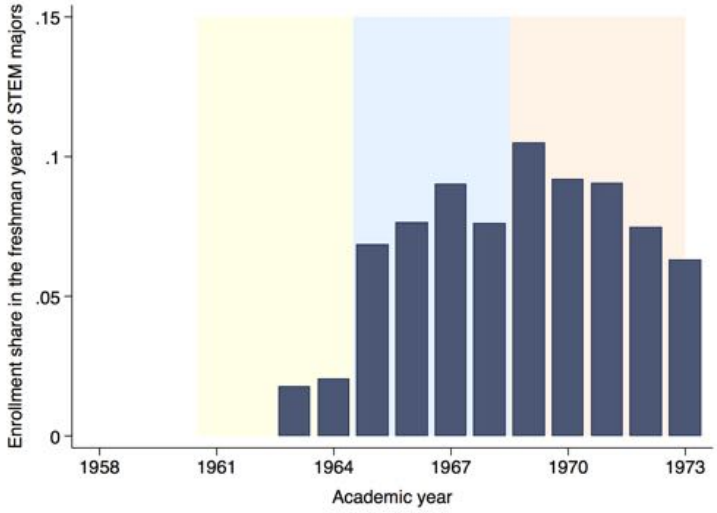


Notes: Headlines of the national newspaper *La Stampa* on the lack of STEM skills in the Italian economy, *http://www.lastampa.it/archivio-storico/*. 10/04/1956: "Too many lawyers and not enough engineers in the era of the machine." 01/13/1957: "Italy lacks technicians for the new industrial era." 11/07/1963: "The big problem of the insufficient engineers for the modern necessities." 08/19/1967: "The Italian industry needs high-skilled workers more than blue-collar workers."

Figure A2: Total Enrollment in the Freshman Year of University STEM Majors in Italy



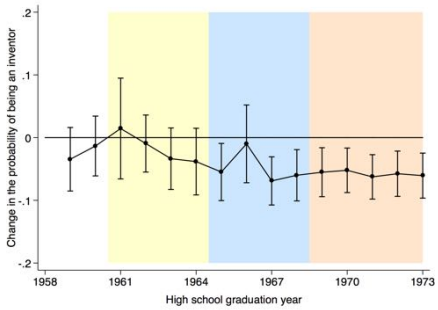
A. All Students



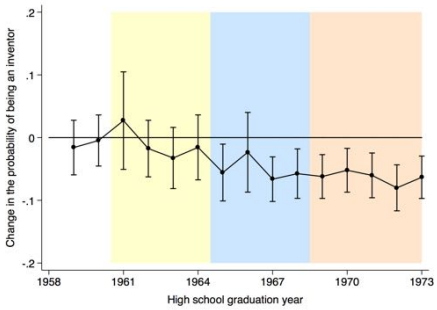
B. Industrial Students

Notes: These graphs show the enrollment change in university STEM majors. In the first panel, the total number of students enrolled in the freshman year of university STEM majors is divided by the total number of high school graduates in the corresponding year. The 1962 observation is missing. In the second panel, the total number of industrial students enrolled in the freshman year of university STEM majors is divided by the total number of high school graduates. The 1961 and 1962 observations are missing. Data coverage: all Italian universities. Source: Annals of Education Statistics, ISTAT.

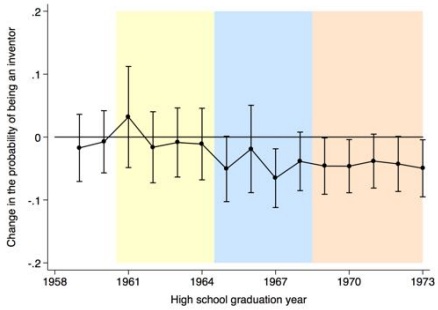
Figure A3: Cohort-Specific Variation in the Probability of Being a Patent Owner



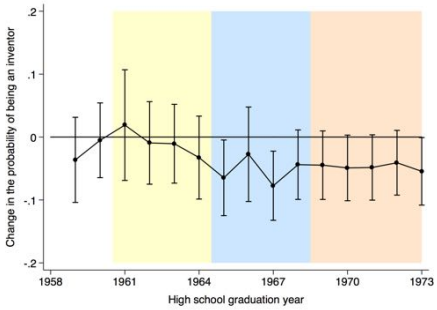
A. Top Industrial vs Top Academic Students



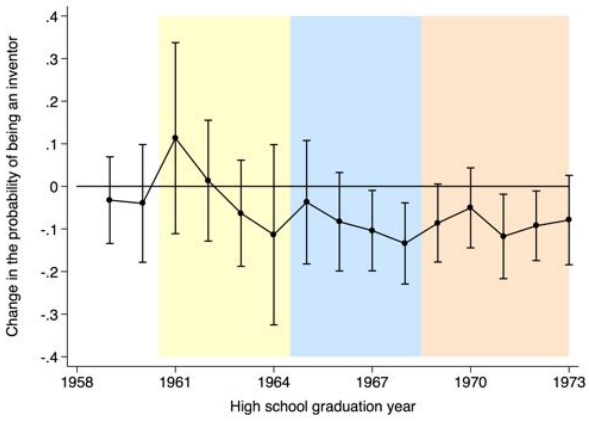
B. Top Industrial vs Top Commercial Students



C. Top vs Other Industrial Students



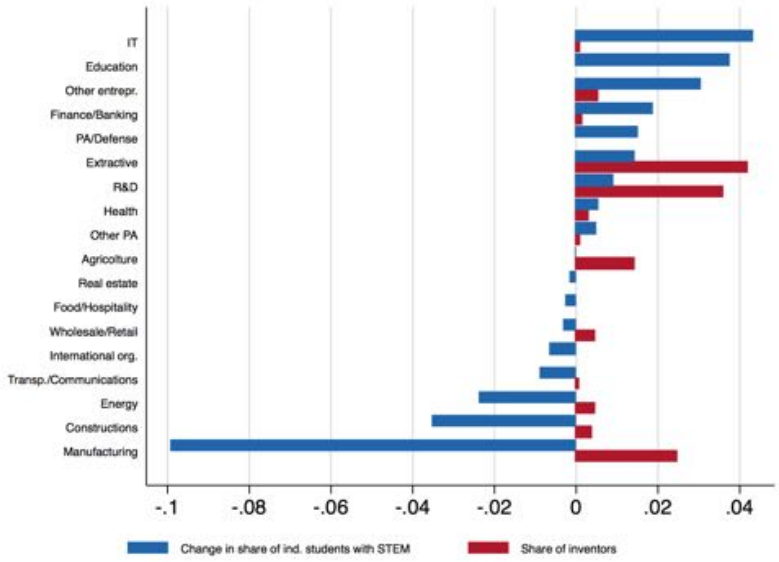
D. Top vs Other, Industrial vs Academic Students



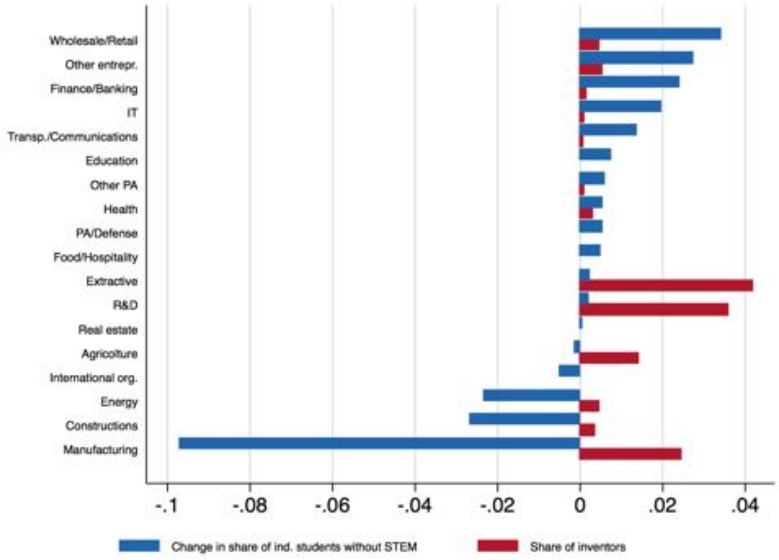
E. Matched, Top Industrial vs Top Academic Students

Notes: Panel A compares industrial and academic students, using only students in the top quartile of their HS class. Panel A compares top industrial and commercial students. Panel C compares top and other industrial students. Panel D compares industrial and academic students with different HS achievement. Panel E compares top industrial and academic students, using only the pre-period students matched to the post-period students with a STEM degree.

Figure A4: Distribution of Inventors across Industries in the Private Sector



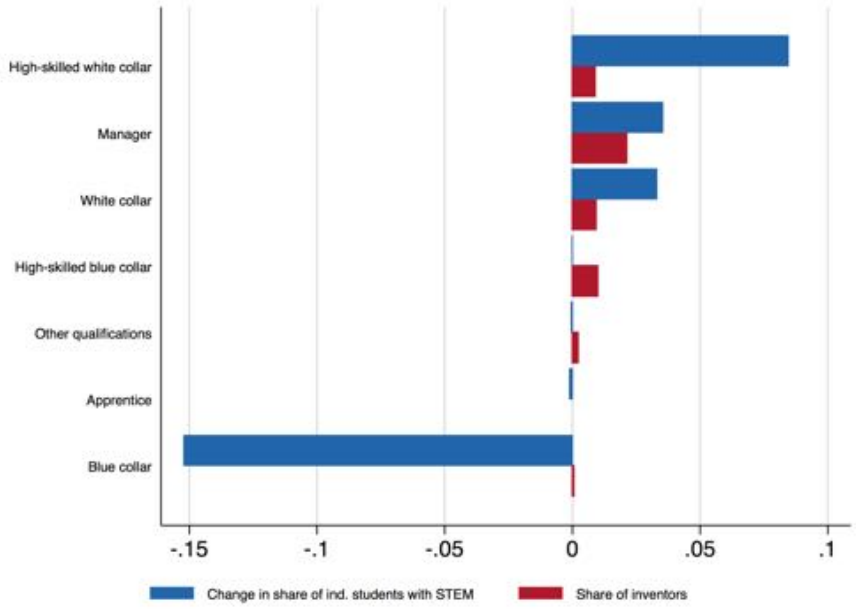
A. Change for Industrial Students with a STEM Degree



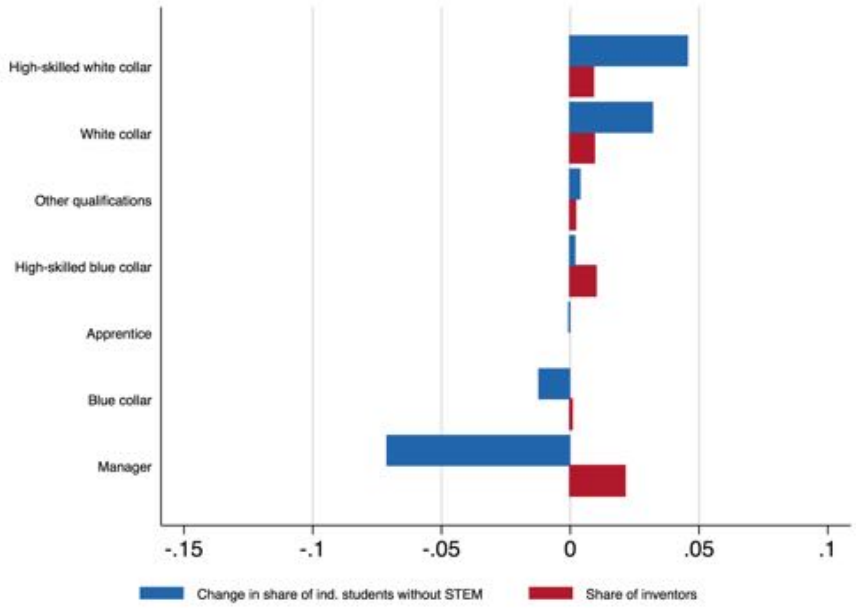
B. Change for Industrial Students without a STEM Degree

Notes: These graphs show how the distribution of industrial students across different industries in the private sector changed among the cohorts who completed high school after 1961. Panel A shows how the distribution of industrial students who received a STEM degree after 1961 changed, relative to the pre-reform distribution. Panel B shows how the distribution of industrial students who did not receive a STEM degree after 1961 changed, relative to the pre-reform distribution. Share of inventors measures the percentage of inventors in each industry, pooling all available years of patent data (1968-2010).

Figure A5: Distribution of Inventors across Positions within the Private Sector



A. Change for Industrial Students with a STEM Degree



B. Change for Industrial Students without a STEM Degree

Notes: These graphs show how the distribution of industrial students across different positions within the private sector changed among the cohorts who completed high school after 1961. Panel A shows how the distribution of industrial students who received a STEM degree after 1961 changed, relative to the pre-reform distribution. Panel B shows how the distribution of industrial students who did not receive a STEM degree after 1961 changed, relative to the pre-reform distribution. Share of inventors measures the percentage of inventors in each qualification, pooling all available years of patent data (1968-2010).

Table A1: Types of Occupation

Occupation	Description	Pension fund	Share of workers
Other private	Employees in the private sector (not included in any other category)	INPS	64.44
Entrepreneurs	Entrepreneurs (imprenditori commerciali)	INPS	5.88
Artisans	Artisans (imprenditori artigiani)	INPS	2.26
Fixed-term contractors	External contractors with fixed-term contracts	INPS	6.51
Farmers	Farmers	INPS	0.43
Other professionals	Other self-employed professionals not included in other categories	INPS	1.69
PA: Local gov.	Public employees of local governments	INPDAP	0.91
PA: Central gov.	Public employees of central government	INPDAP	1.94
PA: Higher ed.	Employees of universities	INPDAP	1.17
PA: Lower ed.	Employees of primary and secondary schools	INPDAP	0.09
PA: Health	Employees of hospitals (not doctors)	INPDAP	1.62
PA: Defense	Employees in the military or police forces	INPDAP	0.02
PA: Research	Employees of CNR (National Research Council)	INPDAP	0.06
PA: Other public	Public employees not included in other categories	INPDAP	0.09
Doctors	Medical doctors and dentists	ENPAM	6.44
Pharmacists	Pharmacists	ENPAF	0.47
Entertainment	Workers in the entertainment industry	ENPALS	0.67
TLC	Employees of TLC companies	Fondo telefonici	0.58
Railway Ind.	Employees of railway companies	Fondo ferrovieri	0.12
Journalists	Journalists	INPGI	0.14
Postal service	Employees of the national postal service	Fondo postali	0.10
Transport Ind.	Employees of local transportation companies	Fondo autoferrotramvieri	0.25
Psychologists	Psychologists	ENPAP	0.20
Veterinarians	Veterinarians	ENPAV	0.22
Chem., agron., geol.	Chemists, agronomists, and geologists	EPAP	0.04
Lawyers	Lawyers	Cassa forense	0.40
Accountants	Self-employed accountants with a commercial diploma	Cassa ragionieri	0.16
Tax collectors	Tax collectors	Fondo esattoriali	0.01
Priests	Priests	Fondo clero	0.10
Engineers and architects	Self-employed engineers and architects	INARCASSA	0.60
Oil/Gas	Gas fitters	Fondo gasisti	0.02
Notaries	Notaries	Cassa del notariato	0.07
Nurses	Nurses (not employed in the public sector)	ENPAPI	0.01
Biologists	Biologists	ENPAB	0.03
Lab. consultants	Labor consultants	ENPACL	0.17
Chart. account.	Chartered accountants with a university degree in business economics	CNPADC	0.13
Airline Ind.	Employees of airline companies	Fondo volo	0.07
Ind. Technicians	High-skilled industrial technicians with an industrial diploma	EPPI	0.18
Surveyors	Surveyors	Cassa geometri	0.26
Energy	Employees of energy/electrical companies	Fondo elettrici	0.64

Notes: List of occupations with a description of the included workers, the type of pension fund, and the share of employed workers.

Table A2: University STEM Graduation Rates of Industrial Students

	STEM (1)	STEM (2)	STEM (3)
Panel A: Industrial vs academic students			
Industrial x Post 1961	0.0404**	0.0467**	0.0503**
	(0.0175)	(0.0220)	(0.0210)
Industrial x Post 1965	0.1720***	0.1783***	0.1819***
	(0.0188)	(0.0231)	(0.0221)
Industrial x Post 1969	0.1665***	0.1728***	0.1764***
	(0.0147)	(0.0198)	(0.0186)
Industrial x 1959		-0.0006	
		(0.0268)	
Industrial x 1960		0.0193	
		(0.0281)	
Industrial x Pre-reform trend			0.0097
			(0.0140)
Panel B: Industrial vs commercial students			
Industrial x Post 1961	0.0368***	0.0433***	0.0445***
	(0.0104)	(0.0138)	(0.0133)
Industrial x Post 1965	0.1314***	0.1379***	0.1391***
	(0.0139)	(0.0165)	(0.0162)
Industrial x Post 1969	0.0811***	0.0875***	0.0888***
	(0.0102)	(0.0137)	(0.0132)
Industrial x 1959		0.0039	
		(0.0181)	
Industrial x 1960		0.0139	
		(0.0162)	
Industrial x Pre-reform trend			0.0071
			(0.0081)

Table continues on the next page.

	STEM (1)	STEM (2)	STEM (3)
Panel C: Top vs other industrial students			
Top x Post 1961	0.0815***	0.0997***	0.0917***
	(0.0255)	(0.0229)	(0.0246)
Top x Post 1965	0.1185***	0.1367***	0.1287***
	(0.0217)	(0.0191)	(0.0207)
Top x Post 1969	0.0959***	0.1141***	0.1061***
	(0.0181)	(0.0146)	(0.0165)
Top x 1959		0.0307	
		(0.0199)	
Top x 1960		0.0206	
		(0.0353)	
Top x Pre-reform trend			0.0098
			(0.0175)
Panel D: Matched industrial vs academic students			
Industrial x Post 1961	0.9680***	0.9815***	0.9620***
	(0.0150)	(0.0129)	(0.0189)
Industrial x Post 1965	0.9674***	0.9809***	0.9614***
	(0.0148)	(0.0131)	(0.0187)
Industrial x Post 1969	0.9682***	0.9815***	0.9622***
	(0.0144)	(0.0446)	(0.0185)
Industrial x 1959		0.0502	
		(0.0320)	
Industrial x 1960		-0.0156	
		(0.0130)	
Industrial x Pre-reform trend			-0.0063
			(0.0110)
University STEM graduation, 1958-1960	0.0189	0.0189	0.0189
Observations (panel A)	35,479	35,479	35,479
Observations (panel B)	27,497	27,497	27,497
Observations (panel C)	16,550	16,550	16,550
Observations (panel D)	4,718	4,718	4,718

Notes: The dependent variable is equal to 1 for the students who received a university STEM degree. Top is 1 for the students who ranked in the top quartile of their school's grade distribution. Post 1961 is 1 for the cohorts who graduated between 1961 and 1964, Post 1965 is 1 for the cohorts who graduated between 1965 and 1968, and Post 1969 is 1 for the cohorts who graduated between 1969 and 1973. The regressions include cohort fixed effects, gender, province of birth fixed effects, high school fixed effects, the high school standardized score, the average standardized score of the closest peers in high school, a dummy for home-schooled students, and a dummy for students who graduated high school at 19. Standard errors clustered by school and cohort in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Characteristics of Matched Students

	Top students			Other students		
	1958-1960	1961-1973	Diff.	1958-1960	1961-1973	Diff.
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Industrial students						
HS score	1.6829	1.7466	-0.0637	-0.1704	-0.2234	0.0530
			(0.0933)			(0.0894)
HS peers' mean score	0.1858	0.1340	0.0518	-0.0389	0.0139	-0.0528
			(0.0447)			(0.0371)
Home–schooled	0.0000	0.0034	-0.0034	0.0704	0.0279	0.0425
			(0.0024)			(0.0727)
HS grad at 19	0.9882	0.9949	-0.0067	0.9718	0.9834	-0.0116
			(0.0121)			(0.0118)
Panel B: Academic students						
HS score	1.6643	1.6469	0.0174	-0.3063	-0.2948	-0.0115
			(0.0504)			(0.0282)
HS peers' mean score	0.0561	0.0676	-0.0115	0.0093	-0.0111	0.0204
			(0.0282)			(0.0198)
Home–schooled	0.0182	0.0166	0.0016	0.0228	0.0191	0.0037
			(0.0123)			(0.0090)
HS grad at 19	0.9909	0.9923	-0.0014	0.9577	0.9631	-0.0054
			(0.0071)			(0.0180)

Notes: This table shows the outcome of the process that matched post-reform students with a STEM degree to pre-reform students. For industrial students, we use the matching process to predict who in the pre-reform period would have received a STEM degree in the absence of any restriction to university enrollment. We match post-reform students with a STEM degree to pre-reform students, separately for each quartile of pre-collegiate ability and by pre-reform cohort. The matching is based on a 1-to-1 nearest neighbor algorithm, in which the calipers for each ability quartile are selected to equate the average STEM graduation rate observed in the post-period. The propensity score matching are computed using the observable characteristics listed in the table: gender, high school score, the average score of high school peers, and a dummy for students who completed high school at 19 (the standard age of graduation). For academic students, there is a concern that some students might have decided to enroll in other fields to avoid crowding into STEM majors after the reform, as documented by Bianchi (2016). Starting from the sample of academic students with a STEM degree, we then use a similar matching process to select the academic students with a STEM degree in the pre-period who would have received a STEM degree also in the post-period. Standard errors clustered by high school and cohort in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4: Probability of Becoming an Inventor, Triple Differences

	Inventor (1)	Inventor (2)	Inventor (3)	Inventor (4)	Inventor (5)
Panel A: Top vs other industrial students					
Top x Post 1961	0.0067	0.0032	0.0031	0.0065	0.0025
	(0.0158)	(0.0227)	(0.0226)	(0.0159)	(0.0220)
Top x Post 1965	-0.0346**	-0.0382*	-0.0382*	-0.0348**	-0.0388*
	(0.0137)	(0.0214)	(0.0214)	(0.0137)	(0.0207)
Top x Post 1969	-0.0359***	-0.0394**	-0.0394**	-0.0361***	-0.0400**
	(0.0109)	(0.0198)	(0.0197)	(0.0110)	(0.0189)
Top x Pre-reform trend		-0.0034			
		(0.0130)			
Panel B: Top vs other, industrial vs academic students					
Top x Industrial x Post 1961	0.0057	0.0057	0.0056	0.0051	0.0032
	(0.0186)	(0.0186)	(0.0186)	(0.0187)	(0.0269)
Top x Industrial x Post 1965	-0.0389**	-0.0389**	-0.0390**	-0.0396**	-0.0415
	(0.0164)	(0.0164)	(0.0164)	(0.0164)	(0.0255)
Top x Industrial x Post 1969	-0.0332**	-0.0332**	-0.0333**	-0.0339**	-0.0358
	(0.0140)	(0.0140)	(0.0140)	(0.0141)	(0.0240)
Top x Industrial x Pre-reform trend		-0.0032			
		(0.0061)			
Panel C: Top vs other, industrial vs commercial students					
Top x Industrial x Post 1961	0.0085	0.0085	0.0085	0.0083	0.0111
	(0.0157)	(0.0157)	(0.0157)	(0.0158)	(0.0227)
Top x Industrial x Post 1965	-0.0349**	-0.0349**	-0.0350**	-0.0352**	-0.0324
	(0.0145)	(0.0145)	(0.0145)	(0.0146)	(0.0219)
Top x Industrial x Post 1969	-0.0373***	-0.0373***	-0.0374***	-0.0376***	-0.0348*
	(0.0109)	(0.0109)	(0.0109)	(0.0109)	(0.0197)
Top x Industrial x Pre-reform trend		-0.0014			
		(0.0048)			
Inventor share, top students, 1958-1960	0.0740	0.0740	0.0740	0.0740	0.0740
Pre-trend by quartile of ability	No	No	Yes	No	No
Pre-trend by high school	No	No	No	Yes	No
Pre-trend by school and ability quartile	No	No	No	No	Yes

Notes. This table shows the effect of the promotion of STEM education on the probability of becoming an inventor of industrial students. Panel A shows difference-in-differences estimates that compare top and other industrial students (16,550 observations). Panel B shows difference-in-difference-in-differences estimates comparing industrial and academic students with different high school grades (35,479 observations). Panel C shows difference-in-difference-in-differences estimates comparing industrial and commercial students with different high school grades (27,497 observations). The dependent variable, Inventor, is a dummy that equals one for students who patented at least once from 1968 to 2010. Top is 1 for the students who ranked in the top quartile of their school's grade distribution. Post 1961 is 1 for the cohorts who graduated between 1961 and 1964, Post 1965 is 1 for the cohorts who graduated between 1965 and 1968, and Post 1969 is 1 for the cohorts who graduated between 1969 and 1973. Pre-reform trend is a linear trend for pre-reform cohorts. The regressions also include cohort fixed effects, gender, province of birth fixed effects, high school fixed effects, the high school standardized score, the average standardized score of the closest peers in high school, a dummy for home-schooled students, and a dummy for students who graduated high school at 19 (and likely never repeated a grade). Standard errors clustered by high school and cohort in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Patent Count and Number of Technological Fields

	OLS		Negative binomial		OLS		Negative binomial	
	Patent count	Number fields	Patent count	Number fields	Patent count	Number fields	Patent count	Number fields
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Industrial vs academic students				
Industrial x Post 1961	-0.1316	-0.0186	-0.0045	0.0102	0.0292	0.0042	0.0441	0.0063
	(0.1681)	(0.0325)	(0.1021)	(0.0299)	(0.0619)	(0.0132)	(0.0525)	(0.0130)
Industrial x Post 1965	-0.2665	-0.0752**	-0.1158	-0.0307	0.0342	0.0196	0.0511	0.0168
	(0.1657)	(0.0310)	(0.0872)	(0.0265)	(0.0559)	(0.0125)	(0.0437)	(0.0115)
Industrial x Post 1969	-0.2636*	-0.0876***	-0.0846	-0.0354	-0.0363	-0.0040	0.0237	0.0067
	(0.1530)	(0.0275)	(0.0821)	(0.0256)	(0.0560)	(0.0115)	(0.0449)	(0.0112)
				Panel B: Industrial vs commercial students				
Industrial x Post 1961	-0.1389	-0.0305	0.0039	0.0017	-0.0120	-0.0070	-0.0015	-0.0038
	(0.1632)	(0.0294)	(0.0327)	(0.0128)	(0.0537)	(0.0109)	(0.0577)	(0.0129)
Industrial x Post 1965	-0.3957**	-0.1011***	-0.0956	-0.0291*	-0.0501	-0.0048	-0.0376	-0.0023
	(0.1967)	(0.0319)	(0.0619)	(0.0152)	(0.0467)	(0.0104)	(0.0507)	(0.0117)
Industrial x Post 1969	-0.3328**	-0.1112***	-0.0423	-0.0259**	-0.0906**	-0.0248***	-0.0459	-0.0111
	(0.1552)	(0.0253)	(0.0266)	(0.0111)	(0.0452)	(0.0094)	(0.0516)	(0.0114)
				Panel C: Matched, Industrial vs academic students				
Industrial x Post 1961	0.1205	-0.0020	0.3877	0.0745	1.2811**	0.1924***	1.0234**	0.1655**
	(0.3920)	(0.0959)	(0.5039)	(0.1238)	(0.5040)	(0.0690)	(0.4985)	(0.0751)
Industrial x Post 1965	-0.2929	-0.1568**	-0.3251	-0.1132	0.5466**	0.2020***	0.4941	0.1922***
	(0.3570)	(0.0747)	(0.3367)	(0.0821)	(0.2650)	(0.0560)	(0.3081)	(0.0507)
Industrial x Post 1969	-0.3265	-0.1535**	-0.2739	-0.1178	0.3790	0.1473***	0.4032	0.1202**
	(0.2414)	(0.0656)	(0.2787)	(0.0782)	(0.3007)	(0.0524)	(0.3280)	(0.0512)
Sample	Top	Top	Top	Top	Other	Other	Other	Other
Pre-reform mean dep. var. (panel A-B)	0.2116	0.0695	0.2116	0.0695	0.1736	0.0537	0.1736	0.0537
Pre-reform mean dep. var. (panel C)	0.5647	0.2471	0.5647	0.2471	0.3944	0.0704	0.3944	0.0704
Observations (panel A)	7,662	7,662	7,662	7,662	27,817	27,817	27,817	27,817
Observations (panel B)	5,865	5,865	5,865	5,865	21,632	21,632	21,632	21,632
Observations (panel C)	1,807	1,807	1,807	1,807	2,911	2,911	2,911	2,911

Notes. This table shows difference-in-differences and difference-in-difference-in-differences estimates of the effect of the promotion of STEM education on the number of patents and the number of technological fields. Standard errors clustered by high school and cohort in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Patent Count and Technological Fields, Alternative Specifications

	OLS		Negative binomial	
	Patent count	Number fields	Patent count	Number fields
	(1)	(2)	(3)	(4)
Panel A: Top vs other industrial students (N = 16,550)				
Top x Post 1961	-0.0778	-0.0106	0.0135	0.0011
	(0.1626)	(0.0291)	(0.0377)	(0.0105)
Top x Post 1965	-0.2059	-0.0710**	0.0099	-0.0298***
	(0.1592)	(0.0279)	(0.0659)	(0.0114)
Top x Post 1969	-0.2029	-0.0731***	-0.0213	-0.0243**
	(0.1542)	(0.0252)	(0.0350)	(0.0113)
Panel B: Top vs other, industrial vs academic students (N = 35,479)				
Top x Industrial x Post 1961	-0.1320	-0.0094	-0.0421	0.0011
	(0.1679)	(0.0324)	(0.0565)	(0.0138)
Top x Industrial x Post 1965	-0.2895*	-0.0800**	-0.1026*	-0.0364***
	(0.1655)	(0.0311)	(0.0531)	(0.0134)
Top x Industrial x Post 1969	-0.2093	-0.0716**	-0.0542	-0.0258**
	(0.1576)	(0.0281)	(0.0524)	(0.0121)
Panel C: Top vs other, industrial vs commercial students (N = 27,497)				
Top x Industrial x Post 1961	-0.1035	-0.0108	0.0075	0.0078
	(0.1647)	(0.0292)	(0.0629)	(0.0127)
Top x Industrial x Post 1965	-0.3198	-0.0822**	-0.1469	-0.0393*
	(0.1961)	(0.0323)	(0.1459)	(0.0207)
Top x Industrial x Post 1969	-0.2324	-0.0769***	-0.0308	-0.0223*
	(0.1583)	(0.0258)	(0.0618)	(0.0122)
Mean dep. var., 1958-1960	0.2116	0.0695	0.2116	0.0695

Notes. This table shows difference-in-differences and difference-in-difference-in-differences estimates of the effect of the promotion of STEM education on the number of patents and the number of technological fields. Standard errors clustered by high school and cohort in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Patent Count and Fields, Only Inventors

	OLS		Negative binomial		OLS		Negative binomial	
	Patent count	Number fields	Patent count	Number fields	Patent count	Number fields	Patent count	Number fields
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Industrial vs academic students				
Industrial x Post 1961	-3.0275	-0.0340	-1.5848	0.0400	2.0156	0.2848	1.9397	0.2034
	(2.6644)	(0.3904)	(1.8703)	(0.3214)	(1.8993)	(0.2437)	(1.6102)	(0.2383)
Industrial x Post 1965	-3.7182	0.0151	-3.6770	-0.4252	0.6981	0.0956	1.2816	0.0968
	(3.7175)	(0.5308)	(2.3891)	(0.3970)	(1.6560)	(0.2321)	(1.3545)	(0.2249)
Industrial x Post 1969	-2.2442	-0.3469	-1.2659	-0.4446	-1.4271	0.0663	-0.5597	0.0287
	(2.7902)	(0.4248)	(1.7991)	(0.3834)	(2.3235)	(0.2122)	(1.8591)	(0.1984)
				Panel B: Industrial vs commercial students				
Industrial x Post 1961	-0.4808	-0.3036	-3.5624**	-0.2218	0.3138	-0.2004	2.9514	0.0332
	(1.7391)	(0.3655)	(1.6077)	(0.1958)	(1.7841)	(0.3152)	(2.7724)	(0.3584)
Industrial x Post 1965	-21.0997*	-3.5426**	-29.9035***	-3.1978***	0.9432	-0.1352	-1.2455	-0.4262
	(10.9561)	(1.3583)	(6.1958)	(0.4970)	(2.9279)	(0.4842)	(2.9503)	(0.3814)
Industrial x Post 1969	-2.5871	-0.4864	-1.3250	0.1175	1.4479	-0.0239	1.2334	-0.0826
	(1.8948)	(0.3456)	(1.5431)	(0.4153)	(1.8612)	(0.2657)	(2.7957)	(0.3600)
				Panel C: Matched, Industrial vs academic students				
Industrial x Post 1961	1.4758	0.3502	0.5402	0.0858	4.8394	1.2168**	8.8683*	0.9999***
	(4.7831)	(1.0429)	(2.6179)	(0.4839)	(4.9055)	(0.4841)	(4.5164)	(0.3624)
Industrial x Post 1965	-0.6212	0.1187	-2.2927	-0.4378	3.6124	1.3691**	2.0021	0.9463***
	(7.4695)	(1.2667)	(3.6286)	(0.6404)	(4.5608)	(0.5682)	(3.5201)	(0.3062)
Industrial x Post 1969	2.5628	0.4109	-0.6669	-0.3546	1.7421	1.3546**	1.1664	0.8530***
	(3.8929)	(0.9643)	(2.3763)	(0.5857)	(5.2830)	(0.5363)	(3.9970)	(0.3168)
Sample	Top	Top	Top	Top	Other	Other	Other	Other
Pre-reform mean dep. var. (panel A-B)	4.84	1.76	4.84	1.76	5.02	1.56	5.02	1.56
Pre-reform mean dep. var. (panel C)	4.8	2.1	4.8	2.1	7	1.25	7	1.25
Observations (panel A)	247	247	247	247	587	587	587	587
Observations (panel B)	169	169	169	169	422	422	422	422
Observations (panel C)	121	121	121	121	194	194	194	194

Notes. This table shows difference-in-differences and difference-in-difference-in-differences estimates of the effect of the promotion of STEM education on the number of patents and the number of technological fields. Standard errors clustered by high school and cohort in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A8: Patent Count and Fields, Alternative Specifications, Only Inventors

	OLS		Negative binomial	
	Patent count	Number fields	Patent count	Number fields
	(1)	(2)	(3)	(4)
Panel A: Top vs other industrial students (N = 557)				
Top x Post 1961	-1.3590	-0.1655	-0.5581	-0.2406
	(2.6264)	(0.2486)	(1.4015)	(0.2043)
Top x Post 1965	-0.5698	-0.0606	0.5513	-0.1246
	(2.8921)	(0.2973)	(1.4372)	(0.2407)
Top x Post 1969	-1.5401	-0.2394	0.0589	-0.1889
	(2.8637)	(0.2438)	(1.4329)	(0.1970)
Panel B: Top vs other, industrial vs academic students (N = 834)				
Top x Industrial x Post 1961	-3.3545	-0.0700	-3.3149	-0.1522
	(2.8509)	(0.3996)	(2.1289)	(0.3501)
Top x Industrial x Post 1965	-3.4335	-0.1238	-3.9375*	-0.4321
	(3.6413)	(0.5094)	(2.3632)	(0.4301)
Top x Industrial x Post 1969	-1.9403	-0.4962	-0.2696	-0.4008
	(3.2091)	(0.4307)	(2.4381)	(0.4034)
Panel C: Top vs other, industrial vs commercial students (N = 591)				
Top x Industrial x Post 1961	-0.9332	-0.1956	-5.2817*	-0.1814
	(6.2144)	(0.9415)	(3.1709)	(0.3919)
Top x Industrial x Post 1965	-22.2802***	-2.3927**	-16.6044*	-1.9620*
	(8.4198)	(0.9540)	(9.5941)	(1.0936)
Top x Industrial x Post 1969	-3.2359	-0.2502	-2.4220	0.2259
	(2.0181)	(0.6292)	(3.3014)	(0.5226)
Mean dep. var., 1958-1960	4.84	1.76	4.84	1.76

Notes. This table shows difference-in-differences and difference-in-difference-in-differences estimates of the effect of the promotion of STEM education on the number of patents and the number of technological fields. Standard errors clustered by high school and cohort in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A9: Probability of Becoming an Inventor of Non-Industrial Students

	Inventor	Inventor	Patent count	Patent count	Number fields	Number fields
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Academic students			
Top x Post 1961	0.0014	0.0019	0.0583	0.0306	-0.0015	-0.0117
	(0.0100)	(0.0145)	(0.0515)	(0.0514)	(0.0155)	(0.0209)
Top x Post 1965	0.0043	0.0049	0.0874*	0.0598	0.0101	-0.0001
	(0.0089)	(0.0137)	(0.0508)	(0.0496)	(0.0139)	(0.0197)
Top x Post 1969	-0.0023	-0.0017	-0.0017	-0.0293	-0.0020	-0.0122
	(0.0088)	(0.0138)	(0.0367)	(0.0348)	(0.0128)	(0.0190)
Top x Pre-reform trend		0.0006		-0.0268		-0.0099
		(0.0090)		(0.0472)		(0.0142)
			Panel B: Commercial students			
Top x Post 1961	-0.0025	-0.0077	0.0134	0.0011	-0.0019	-0.0077
	(0.0040)	(0.0068)	(0.0121)	(0.0133)	(0.0046)	(0.0070)
Top x Post 1965	0.0019	-0.0033	0.1272	0.1149	0.0149	0.0091
	(0.0053)	(0.0075)	(0.1211)	(0.1181)	(0.0167)	(0.0171)
Top x Post 1969	0.0008	-0.0044	0.0155	0.0032	0.0013	-0.0045
	(0.0039)	(0.0067)	(0.0123)	(0.0137)	(0.0043)	(0.0069)
Top x Pre-reform trend		-0.0047		-0.0111		-0.0052
		(0.0037)		(0.0068)		(0.0037)

Notes: Panel A uses data of academic students (18,929 observations), while panel B uses data of commercial students (10,497 observations). The dependent variable Inventor is 1 if the student developed at least 1 patent,Patent count is the number of patents developed, and Number fields is the number of different technological fields (classes of invention) per inventor. Top is 1 for the students who ranked in the top quartile of their school's grade distribution. . Post 1961 is 1 for the cohorts who graduated between 1961 and 1964, Post 1965 is 1 for the cohorts who graduated between 1965 and 1968, and Post 1969 is 1 for the cohorts who graduated between 1969 and 1973. Pre-reform trend is a linear pre-reform trend. The regressions also include cohort fixed effects, gender, province of birth fixed effects, high school fixed effects, the high school standardized score, the average standardized score of the closest peers in high school, a dummy for home-schooled students, and a dummy for students who graduated high school at 19 (and likely never repeated a grade). Standard errors clustered by high school and cohort in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A10: Effects on Innovation, Robustness Checks

	Inventor (1)	Inventor (2)	Inventor (3)	Inventor (4)	Inventor (5)	Inventor (6)	Inventor (7)	Inventor (8)
				Panel A: Industrial vs academic students				
Industrial x Post 1961	0.0171	-0.0085	-0.0058	-0.0215*	0.0049	-0.0036	-0.0019	-0.0001
	(0.0321)	(0.0152)	(0.0180)	(0.0115)	(0.0161)	(0.0048)	(0.0056)	(0.0047)
Industrial x Post 1965	-0.0254	-0.0476*	-0.0385***	-0.0342***	0.0281*	0.0132**	0.0127**	0.0138***
	(0.0269)	(0.0248)	(0.0142)	(0.0103)	(0.0149)	(0.0066)	(0.0063)	(0.0049)
Industrial x Post 1969	-0.0301		-0.0432***	-0.0428***	0.0110		-0.0010	-0.0005
	(0.0256)		(0.0113)	(0.0088)	(0.0142)		(0.0051)	(0.0041)
				Panel B: Industrial vs commercial students				
Industrial x Post 1961	0.0172	-0.0136	0.0002	-0.0143	-0.0063	-0.0073*	-0.0038	-0.0038
	(0.0287)	(0.0136)	(0.0150)	(0.0106)	(0.0149)	(0.0038)	(0.0043)	(0.0035)
Industrial x Post 1965	-0.0501*	-0.0594**	-0.0428***	-0.0357***	0.0033	0.0019	-0.0020	0.0048
	(0.0268)	(0.0242)	(0.0123)	(0.0099)	(0.0139)	(0.0061)	(0.0050)	(0.0041)
Industrial x Post 1969	-0.0578***		-0.0586***	-0.0465***	-0.0097		-0.0134***	-0.0066**
	(0.0223)		(0.0090)	(0.0084)	(0.0131)		(0.0039)	(0.0031)
				Panel C: Matched, Industrial vs academic students				
Industrial x Post 1961	0.0469	-0.0452		-0.0438	0.0966*	0.0814*		0.0354
	(0.0674)	(0.0492)		(0.0406)	(0.0577)	(0.0430)		(0.0316)
Industrial x Post 1965	-0.0513	-0.0471		-0.0776***	0.1263***	0.1471***		0.0597**
	(0.0441)	(0.0748)		(0.0262)	(0.0412)	(0.0465)		(0.0272)
Industrial x Post 1969	-0.0515			-0.0777***	0.0731*			0.0125
	(0.0449)			(0.0241)	(0.0438)			(0.0250)
Specification	Probit	Pre-1966	Weights	29-56	Probit	Pre-1966	Weights	29-56
Sample	Top	Top	Top	Top	Other	Other	Other	Other

Notes. This table shows additional evidence on the effect of the promotion of STEM education on the probability of becoming an inventor. Columns 1 and 5 show marginal effects from a probit regression. Columns 2 and 6 restrict the sample to cohorts who completed high school before 1966. Columns 3 and 7 use sampling weights to keep the average student characteristics constant at the pre-reform levels. Columns 4 and 8 consider only the inventors who developed at least one patent between the age of 29 and 56. Standard errors clustered by high school and cohort in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A11: Effects on Innovation, Robustness Checks for Alternative Specifications

	Inventor (1)	Inventor (2)	Inventor (3)	Inventor (4)
Panel A: Top vs other industrial students				
Top x Post 1961	0.0073	0.0031	0.0086	-0.0093
	(0.0151)	(0.0157)	(0.0171)	(0.0112)
Top x Post 1965	-0.0465***	-0.0449**	-0.0360**	-0.0359***
	(0.0153)	(0.0194)	(0.0149)	(0.0101)
Top x Post 1969	-0.0391***		-0.0354***	-0.0355***
	(0.0117)		(0.0117)	(0.0085)
Panel B: Top vs other, industrial vs academic students				
Top x Industrial x Post 1961	0.0081	0.0017	0.0035	-0.0171
	(0.0217)	(0.0187)	(0.0197)	(0.0132)
Top x Industrial x Post 1965	-0.0524***	-0.0526**	-0.0423**	-0.0448***
	(0.0197)	(0.0224)	(0.0176)	(0.0119)
Top x Industrial x Post 1969	-0.0364***		-0.0348**	-0.0394***
	(0.0173)		(0.0149)	(0.0102)
Panel C: Top vs other, industrial vs commercial students				
Top x Industrial x Post 1961	0.0202	0.0055	0.0108	-0.0059
	(0.0194)	(0.0156)	(0.0163)	(0.0115)
Top x Industrial x Post 1965	-0.0418**	-0.0471**	-0.0324**	-0.0370***
	(0.0198)	(0.0206)	(0.0153)	(0.0117)
Top x Industrial x Post 1969	-0.0347**		-0.0375***	-0.0372***
	(0.0147)		(0.0116)	(0.0093)
Specification	Probit	Pre-1966	Weights	29-56

Notes. This table shows additional evidence on the effect of the promotion of STEM education on the probability of becoming an inventor. Column 1 shows marginal effects from a probit regression. Column 2 restricts the sample to cohorts who completed high school before 1966. Column 3 uses sampling weights to keep the average student characteristics constant at the pre-reform levels. Column 4 considers only the inventors who developed at least one patent between the age of 29 and 56. Standard errors clustered by high school and cohort in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A12: Probability of Becoming an Inventor, US Patents

	Inventor (1)	C–W patents (2)	Inventor (3)	C–W patents (4)	Inventor (5)	C–W patents (6)
			Panel A: Industrial vs academic students			
Industrial x Post 1961	-0.0026	0.0077	-0.0076	-0.1030	-0.0017	0.0270
	(0.0046)	(0.1282)	(0.0117)	(0.3021)	(0.0040)	(0.1426)
Industrial x Post 1965	-0.0014	-0.1087	-0.0039	-0.1367	-0.0014	-0.1138
	(0.0037)	(0.1010)	(0.0091)	(0.2828)	(0.0038)	(0.1233)
Industrial x Post 1969	-0.0074**	-0.1562	-0.0137*	-0.1914	-0.0056	-0.1435
	(0.0034)	(0.1001)	(0.0075)	(0.2754)	(0.0036)	(0.1254)
			Panel B: Industrial vs commercial students			
Industrial x Post 1961	-0.0034	-0.0169	-0.0050	-0.0959	-0.0038	-0.0107
	(0.0043)	(0.1154)	(0.0099)	(0.2668)	(0.0035)	(0.1236)
Industrial x Post 1965	-0.0085**	-0.2221***	-0.0148	-0.3068	-0.0075**	-0.2093**
	(0.0035)	(0.0844)	(0.0089)	(0.2675)	(0.0033)	(0.1002)
Industrial x Post 1969	-0.0124***	-0.2457***	-0.0197***	-0.3689	-0.0108***	-0.2199**
	(0.0032)	(0.0827)	(0.0067)	(0.2501)	(0.0031)	(0.1020)
			Panel C: Matched, Industrial vs academic students			
Industrial x Post 1961	0.0605**	2.1984***	0.0620	1.9570**	0.0477*	2.4805**
	(0.0289)	(0.6720)	(0.0426)	(0.8613)	(0.0280)	(1.2032)
Industrial x Post 1965	0.0354**	0.7425**	0.0026	0.6777	0.0528**	0.8385
	(0.0177)	(0.3519)	(0.0299)	(0.5321)	(0.0212)	(0.5349)
Industrial x Post 1969	0.0138	0.5277	-0.0168	0.3220	0.0368*	0.7505
	(0.0147)	(0.3584)	(0.0249)	(0.4300)	(0.0197)	(0.5880)
Sample	All	All	Top	Top	Other	Other
Pre-reform dep. var. (panels A-B)	0.0183	0.3409	0.0237	0.4379	0.0169	0.3157
Pre-reform dep. var. (panel C)	0.0321	0.3333	0.0353	0.2823	0.0282	0.3944
Observations (panel A)	35,479	35,479	7,662	7,662	27,817	27,817
Observations (panel B)	27,497	27,497	5,865	5,865	21,632	21,632
Observations (panel C)	4,718	4,718	1,807	1,807	2,911	2,911

Notes. This table shows the effect of the promotion of STEM education on the probability of developing at least one patent issued by the US Patent Office. The source of US patent data is the NBER US Patent Citation Data File (Hall, Jaffe and Trajtenberg, 2001). Columns 3 and 4 restrict the sample to students who ranked in the top quartile of their school's grade distribution. Columns 5 and 6 restrict the sample to students who are not in the top ability quartile. The regressions also include cohort fixed effects, gender, province of birth fixed effects, high school fixed effects, the high school standardized score, the average standardized score of the closest peers in high school, a dummy for home-schooled students, and a dummy for students who graduated high school at 19 (and likely never repeated a grade). Standard errors clustered by high school and cohort in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A13: Unverified Inventors

	Inventor Verified (1)	Inventor Pr > 90% (2)	Inventor Pr> 75% (3)	Inventor Pr >60% (4)	Inventor Pr> 50% (5)	Inventor Pr >40% (6)	Inventor Pr >25% (7)	Inventor All (8)
Panel A: Top industrial vs top academic students								
Industrial x Post 1961	-0.0002	-0.0002	-0.0002	-0.0002	-0.0008	-0.0007	0.0011	0.0344
	(0.0172)	(0.0172)	(0.0172)	(0.0171)	(0.0171)	(0.0173)	(0.0174)	(0.0221)
Industrial x Post 1965	-0.0317**	-0.0317**	-0.0317**	-0.0307**	-0.0268*	-0.0272*	-0.0175	-0.0124
	(0.0144)	(0.0144)	(0.0144)	(0.0142)	(0.0145)	(0.0147)	(0.0150)	(0.0222)
Industrial x Post 1969	-0.0403***	-0.0403***	-0.0403***	-0.0398***	-0.0394***	-0.0374***	-0.0342***	-0.0534***
	(0.0120)	(0.0120)	(0.0120)	(0.0119)	(0.0120)	(0.0122)	(0.0127)	(0.0194)
Panel B: Top industrial vs top commercial students								
Industrial x Post 1961	-0.0039	-0.0039	-0.0039	-0.0038	-0.0031	-0.0030	-0.0015	0.0269
	(0.0147)	(0.0147)	(0.0147)	(0.0146)	(0.0147)	(0.0148)	(0.0152)	(0.0224)
Industrial x Post 1965	-0.0420***	-0.0420***	-0.0420***	-0.0407***	-0.0357***	-0.0330**	-0.0242*	-0.0300
	(0.0127)	(0.0127)	(0.0127)	(0.0124)	(0.0128)	(0.0129)	(0.0133)	(0.0214)
Industrial x Post 1969	-0.0559***	-0.0559***	-0.0559***	-0.0563***	-0.0551***	-0.0523***	-0.0496***	-0.0758***
	(0.0097)	(0.0097)	(0.0097)	(0.0096)	(0.0098)	(0.0102)	(0.0108)	(0.0199)
Panel C: Top vs other industrial students								
Top x Post 1961	0.0067	0.0066	0.0066	0.0061	0.0056	0.0053	0.0064	0.0271
	(0.0158)	(0.0159)	(0.0159)	(0.0159)	(0.0159)	(0.0158)	(0.0156)	(0.0216)
Top x Post 1965	-0.0346**	-0.0347**	-0.0347**	-0.0336**	-0.0300**	-0.0284**	-0.0268**	-0.0393*
	(0.0137)	(0.0137)	(0.0137)	(0.0135)	(0.0138)	(0.0139)	(0.0134)	(0.0202)
Top x Post 1969	-0.0359***	-0.0361***	-0.0363***	-0.0359***	-0.0359***	-0.0351***	-0.0350***	-0.0451**
	(0.0109)	(0.0109)	(0.0109)	(0.0110)	(0.0110)	(0.0110)	(0.0106)	(0.0185)
Panel D: Top vs other, industrial vs academic students								
Top x Industrial x Post 1961	0.0057	0.0056	0.0056	0.0051	0.0037	0.0028	0.0066	0.0349
	(0.0186)	(0.0186)	(0.0186)	(0.0187)	(0.0187)	(0.0187)	(0.0185)	(0.0248)
Top x Industrial x Post 1965	-0.0389**	-0.0390**	-0.0390**	-0.0376**	-0.0348**	-0.0361**	-0.0291*	-0.0320
	(0.0164)	(0.0164)	(0.0164)	(0.0162)	(0.0164)	(0.0167)	(0.0160)	(0.0233)
Top x Industrial x Post 1969	-0.0332**	-0.0335**	-0.0331**	-0.0328**	-0.0329**	-0.0334**	-0.0323**	-0.0352
	(0.0140)	(0.0140)	(0.0140)	(0.0140)	(0.0140)	(0.0141)	(0.0137)	(0.0217)
Panel E: Matched, Top industrial vs top academic students								
Industrial x Post 1961	-0.0044	-0.0044	-0.0044	-0.0044	-0.0032	-0.0036	0.0019	0.0882
	(0.0501)	(0.0501)	(0.0501)	(0.0501)	(0.0501)	(0.0501)	(0.0511)	(0.0627)
Industrial x Post 1965	-0.0679**	-0.0679**	-0.0679**	-0.0679**	-0.0513	-0.0555	-0.0377	0.0254
	(0.0334)	(0.0334)	(0.0334)	(0.0334)	(0.0353)	(0.0356)	(0.0385)	(0.0426)
Industrial x Post 1969	-0.0629**	-0.0629**	-0.0629**	-0.0629**	-0.0614**	-0.0620**	-0.0687**	-0.0516
	(0.0296)	(0.0296)	(0.0296)	(0.0296)	(0.0295)	(0.0295)	(0.0329)	(0.0401)
Number of Inventors	869	870	874	880	901	934	1,067	2,399

Notes: Different columns include a different amount of unverified inventors (inventors whose patents could not be verified though the fiscal code or an internet search) in the sample. Column 1 includes only the verified inventors, column 2 all the inventors with an estimated probability above 90 percent, column 3 above 75 percent, column 4 above 60 percent, column 5 above 50 percent, column 6 above 40 percent, and column 7 above 25 percent. Column 8 includes all unverified inventors. Standard errors clustered by high school and cohort in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A14: Industries Within the Private Sector

	R&D	Manufacturing	Education	Other public	Top pay	R&D	Manufacturing	Education	Other public	Top pay
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					Panel A: Industrial vs academic students					
Industrial x Post 1961	-0.0067	-0.1396**	0.0161	0.0413***	0.0367	0.0116	-0.0174	-0.0104	-0.0056	0.0248
	(0.0100)	(0.0555)	(0.0142)	(0.0148)	(0.0381)	(0.0073)	(0.0306)	(0.0074)	(0.0087)	(0.0233)
Industrial x Post 1965	0.0014	0.0048	-0.0091	0.0201	0.0121	0.0181**	0.0241	-0.0061	-0.0110	-0.0100
	(0.0057)	(0.0534)	(0.0139)	(0.0153)	(0.0372)	(0.0077)	(0.0290)	(0.0072)	(0.0082)	(0.0223)
Industrial x Post 1969	0.0037	-0.0184	-0.0018	0.0139	0.0170	0.0167**	0.0497*	-0.0134**	-0.0115	-0.0028
	(0.0048)	(0.0498)	(0.0130)	(0.0137)	(0.0351)	(0.0068)	(0.0272)	(0.0067)	(0.0077)	(0.0215)
					Panel B: Matched, Industrial vs academic students					
Industrial x Post 1961	-0.0010	-0.3373***	0.0380**	0.0616**	0.0617	0.0769*	-0.0391	0.0129	0.0429	0.0229
	(0.0193)	(0.0943)	(0.0190)	(0.0257)	(0.0555)	(0.0421)	(0.1028)	(0.0206)	(0.0373)	(0.0560)
Industrial x Post 1965	0.0126	-0.1433*	0.0095	0.0337	0.0828*	0.0527**	0.0010	0.0070	0.0142	0.0276
	(0.0164)	(0.0770)	(0.0131)	(0.0231)	(0.0487)	(0.0205)	(0.0745)	(0.0103)	(0.0088)	(0.0405)
Industrial x Post 1969	0.0070	-0.1563**	0.0226**	0.0354*	0.0859*	0.0384**	0.0295	0.0143	-0.0003	0.0214
	(0.0115)	(0.0695)	(0.0106)	(0.0215)	(0.0442)	(0.0176)	(0.0718)	(0.0107)	(0.0056)	(0.0404)
Sample	Top	Top	Top	Top	Top	Other	Other	Other	Other	Other
Pre-reform dep. var. (panel A)	0.0000	0.6224	0.0053	0.0012	0.1198	0.0025	0.6286	0.0025	0.0129	0.1195
Pre-reform dep. var. (panel B)	0.0000	0.7622	0.0000	0.0000	0.0458	0.0000	0.7551	0.0041	0.0000	0.0307
Observations (panel A)	76,315	76,315	76,315	76,315	76,315	261,189	261,189	261,189	261,189	261,189
Observations (panel B)	25,528	25,528	25,528	25,528	25,528	42,274	42,274	42,274	42,274	42,274

Notes. This table shows the effect of the promotion of STEM education on the industry choice. Dependent variables: R&D is a dummy for research–intensive industries, Manufacturing is a dummy for all manufacturing industries, Education and Other public are dummies for industries that provide public services (the sample, however, includes only individuals who are employed by companies not directly part of the public administration), Top pay is a dummy for the five industries with the highest average salaries for workers with STEM degrees (Energy, Food/Hospitality, Transportation/Communications, Finance/Banking, and International organizations). Post 1961 is 1 for the cohorts who graduated between 1961 and 1964, Post 1965 is 1 for the cohorts who graduated between 1965 and 1968, and Post 1969 is 1 for the cohorts who graduated between 1969 and 1973. Columns 6 to 10 restrict the sample to students who ranked in the top quartile of their school's grade distribution. The regressions include cohort and calendar year fixed effects, gender, province of birth fixed effects, high school fixed effects, the HS score, the average standardized score of the closest peers in high school, a dummy for home-schooled students, and a dummy for students who graduated high school at 19. Standard errors clustered by student in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A15: Positions Within the Private Sector

	Top pos. (1)	Manager (2)	Top pos. (3)	Manager (4)	Top pos. (5)	Manager (6)	Top pos. (7)	Manager (8)
				Panel A: Industrial vs academic students				
Industrial x Post 1961	-0.0409	-0.0530	-0.0435	-0.0681	0.0140	0.0080	0.0062	0.0104
	(0.0316)	(0.0330)	(0.0480)	(0.0509)	(0.0144)	(0.0149)	(0.0245)	(0.0262)
Industrial x Post 1965	0.0588*	0.0548*	0.0156	0.0223	0.0650***	0.0466***	0.0665***	0.0466*
	(0.0307)	(0.0320)	(0.0461)	(0.0492)	(0.0138)	(0.0142)	(0.0231)	(0.0247)
Industrial x Post 1969	0.0539*	0.0325	0.0075	-0.0174	0.0385***	0.0286**	0.0175	0.0170
	(0.0287)	(0.0295)	(0.0427)	(0.0449)	(0.0129)	(0.0131)	(0.0216)	(0.0229)
				Panel B: Matched, Industrial vs academic students				
Industrial x Post 1961	0.0702	0.0354	0.0995	0.0519	0.2661***	0.2808***	0.3063***	0.3718***
	(0.0642)	(0.0698)	(0.0934)	(0.1091)	(0.0548)	(0.0602)	(0.0819)	(0.0982)
Industrial x Post 1965	0.1742***	0.1640***	0.1593**	0.1669*	0.3183***	0.2842***	0.3012***	0.2766***
	(0.0552)	(0.0591)	(0.0796)	(0.0906)	(0.0406)	(0.0435)	(0.0684)	(0.0788)
Industrial x Post 1969	0.1866***	0.1257**	0.1481*	0.0960	0.2732***	0.2496***	0.2524***	0.2557***
	(0.0524)	(0.0560)	(0.0769)	(0.0865)	(0.0389)	(0.0415)	(0.0656)	(0.0752)
Sample	Top	Top	Top	Top	Other	Other	Other	Other
Industry f.e.	No	No	Yes	Yes	No	No	Yes	Yes
Pre- reform dep. var. (panel A)	0.2321	0.2182	0.2321	0.2182	0.1486	0.1375	0.1486	0.1375
Pre- reform dep. var. (panel B)	0.2271	0.2075	0.2271	0.2075	0.1462	0.1295	0.1462	0.1295
Observations (Panel A)	161,759	161,759	75,901	75,901	616,783	616,783	259,411	259,411
Observations (Panel B)	45,258	45,258	25,433	25,433	75,347	75,347	42,054	42,054

Notes. This table shows the effect of the promotion of STEM education on the position held within a firm. Dependent variables: Top pos. is a dummy for the two highest positions of manager and higher-level white collar (*quadro* in Italian), and Manager is a dummy for workers in a managerial position. Columns 3, 4, 7, and 8 control for industry fixed effects to capture position changes within the same industries in the private sector. Post 1961 is 1 for the cohorts who graduated between 1961 and 1964, Post 1965 is 1 for the cohorts who graduated between 1965 and 1968, and Post 1969 is 1 for the cohorts who graduated between 1969 and 1973. Columns 5 to 8 restrict the sample to students who ranked in the top quartile of their school's grade distribution. The regressions include cohort and calendar year fixed effects, gender, province of birth fixed effects, high school fixed effects, the HS score, the average standardized score of the closest peers in high school, a dummy for home-schooled students, and a dummy for students who graduated high school at 19. Standard errors clustered by student in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

B Curriculum change in STEM majors

Pursuing a university STEM education affected how students sorted into different occupations. In addition, the human capital acquired in STEM majors changed the technological areas in which the industrial students patented. All these effects are large and significant only among the cohorts who completed high school after 1965, although university STEM graduation rates increased from 1961. In this subsection, we explore a potential explanation for a delay in the effect of STEM education.

Industrial high schools heavily focused on applied STEM disciplines at the expenses of theoretical STEM education. As a result, industrial students enrolled in STEM majors with good practical skills, but lacked a solid theoretical foundation in most STEM areas. To analyze the performance of industrial students during their university studies, we divided all courses in university STEM majors in two categories: industrial courses, which were directly related to the disciplines taught by industrial high schools, and academic courses, which required more theoretical or advanced skills.[21] We then estimated the following specification:

$$g_{icp} = \alpha + \beta_c + \gamma_p + \delta \left(\text{Industrial student}_i \times \text{Industrial course}_c\right) + \eta X_{ip} + u_{icp}, \qquad (5)$$

where g_{icp} is the standardized grade of student i in the STEM course c in academic year p. Industrial student$_i$ is equal to one if student i received an industrial high school diploma. Industrial course$_c$ is equal to one if the course is related to a discipline taught in industrial high schools. X_{ip} denotes student characteristics, such as year of high school graduation fixed effects, gender, and pre-collegiate achievement. β_c are course fixed effects and γ_p are academic year fixed effects. The sample includes academic and industrial students who completed high school between 1958 and 1973 and were enrolled in a STEM major between

[21] Based on the disciplines taught in industrial high schools, we used the following keywords to identify industrial courses: aerodinamica, aeromobili, aeronautica, aerotecnica, antenne, architettura, caldaie, cantieri, centrali, chimica, chimiche, comunicazione, controlli automatici, controlli dei processi, costruttivi, costruzione, costruzioni, disegno, elettriche, elettro, elettronica, elettronici, elettronico, elettrotecnica, elicotteri, estimo, fondazioni, forni, idraulica, idrologia, impianti, infrastrutture, macchinari, macchine, materiali, meccanica, meccaniche, metalli, metallo, motori, plastiche, progetti, progetto, programmazione, propulsione, propulsori, radiochimica, radiotecnica, reattori, regolazione, rilevatori, siderurgia, sintesi, speciali, sismica, sistemi operativi, statica, struttura, strutture, strutturistica, tecnologia, tecnologie, tensioni, topografia. In the engineering major, for example, technical drawing is an industrial course and introductory math is an academic course.

1961 and 1977.

The estimated coefficient of Industrial student$_i$ × Industrial course$_c$ indicates that industrial students scored 0.12 standard deviations above academic students in industrial courses, after controlling for other course and student characteristics (table B1, panel A, column 1). This result is due to the fact that industrial students scored 0.11 standard deviations above the mean in industrial courses (table B1, panel A, column 3), while academic students scored only 0.04 standard deviations below the mean (table B1, panel A, column 4). This finding suggests that industrial students might have experienced a lower accumulation of human capital in STEM majors, because they lacked the required preparation to thrive in academic courses.[22]

From 1969, students could choose courses more freely, instead of complying with the curriculum imposed by the university administration. This reform represented an opportunity for industrial students to select courses that were more in line with their pre-collegiate skills. To test the effect of the 1969 reform on the course choice, we estimated the following specification:

$$\text{Share industrial courses}_{ip} = \alpha + \gamma_p + \sum_p \delta_p \left(\text{Industrial student}_i \times \gamma_p\right) + \eta X_{ip} + u_{ip}, \qquad (6)$$

where Share industrial courses$_{ip}$ is the share of industrial courses attended by student i in the academic year p, γ_p are academic year fixed effects, and X_{ip} are student characteristics.

The difference-in-differences coefficients of Industrial student$_i \times \gamma_p$ indicate that the share of industrial courses in the curriculum of industrial students increased by 7.53 percentage points between 1969 and 1977 (table B1, panel B, column 1). This effect is the result of two diverging trends. After 1969, in fact, industrial students increased the share of industrial courses by 8.05 percentage points (table B1, panel B, column 3), while academic students reduced it by 1.07 percentage points (table B1, panel B, column 4). Although this finding indicates that both academic and industrial students switched to more favorable courses after 1969, the change was much larger among industrial students, whose human capital accumulation was plausibly more penalized by the rigid curricula.

[22]The share of academic courses was equal to 55 percent in an average academic year.

A greater flexibility in the choice of the courses benefited the students who entered into STEM majors after 1969, as well as the students who were enrolled at the time of the implementation. To prove this point, we estimate equation 6 including only the students who completed high school before 1969. In this case, the industrial students increased the share of industrial courses in their curricula by 3.53 percentage points between 1969 and 1977 (table B1, panel B, column 2).

This course–level analysis suggested that the industrial students might have accumulated more human capital after 1969, when they could select a higher number of industrial courses. The same post-1965 cohorts who benefited from a flexible curriculum experienced a change in their innovative output and in their occupational sorting.

Table B1: Industrial Courses and Curriculum Change

	Industrial vs academic	Pre-1969 cohorts	Industrial students	Academic students	Top vs other industrial	Top vs other academic
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Grades in different STEM courses			
Industrial student x Industrial course	0.1216***	0.1616***				
	(0.0144)	(0.0194)				
Industrial course			0.1136***	-0.0409***		
			(0.0108)	(0.0072)		
Top x Industrial course					-0.0407	0.0550*
					(0.0430)	(0.0305)
			Panel B: Share of industrial courses in the curriculum			
Industrial student x 1965–1968	0.0245	0.0145				
	(0.0163)	(0.0163)				
Industrial student x 1969-1977	0.0753***	0.0353**				
	(0.0154)	(0.0161)				
1965–1968			0.0231	-0.0067		
			(0.0157)	(0.0050)		
1969-1977			0.0805***	-0.0107**		
			(0.0152)	(0.0043)		
Top x 1965–1968					-0.0040	0.0029
					(0.0536)	(0.0177)
Top x 1969-1977					-0.0035	0.0161
					(0.0524)	(0.0144)
Observations (panel A)	136,275	93,363	38,297	97,978	38,297	97,978
Observations (panel B)	27,786	18,970	8,294	19,492	8,294	19,492

Notes: Panel A shows how industrial students performed in the industrial courses (close to the curriculum of industrial high schools) of STEM majors. The unit of analysis is a students i in the STEM course c and the academic year p (academic years from 1961 to 1977). Panel B shows how the share of industrial courses increased after 1969 among industrial students. The unit of analysis is a student i in the academic year a (1960–1977). The dependent variable is the standardized course grade in panel A and the share of industrial courses in each academic year in panel B. Standard errors clustered by student in parentheses, *** p<0.01, ** p<0.05, * p<0.1.