Margaux Suteau | Curriculum Vitae

Department of Social Policy – London School of Economics and Political Science
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Positions

LSE Fellow
Department of Social Policy, London School of Economics *Current*

Research Officer
Department of Social Policy, London School of Economics *2022 – 2023*
PARENTIME team with A. Sevilla

Research

Inheritance and Women's Empowerment: the Heterogeneous Effect of Property Rights - R&R - Review of the Economics of the Household

Gendered Objects and STEM Choices: Evidence from France's Free-Computer Programs - Under Review

Empowering Parents in the Digital Age: Mitigating Social Media's Impact on Youth Development - *with Greta Morando and Sonkurt Sen*

Back to the Roots: the Effect of Culture on Post-Secondary Educational Choices - *with Caroline Coly*

The Bystander Issue: Understanding the Role of Beliefs in Workplace Sexual Harassment - *with Caroline Coly, Paola Profeta, and Almudena Sevilla*

Policy Work

The Economic Effects of Sexual Harassment in the Workplace. LSE Public Policy Review. 2025; 3(4): 7, pp. 1–11.- *with Caroline Coly*

Education

CY Cergy Paris Université - ESSEC
PhD Program in Economics, Supervisers: O.Donni & S. Marcassa (THEMA) *2019 - Dec 2023*
Dissertation title: Breaking Barriers: Essays on Gender Inequalities
Jury: Julien Grenet, Hélène Périvier, Thomas Breda, Paola Profeta, Cristina Terra

Sciences Po SGEL - CY Cergy Paris Université - ESSEC
Master Research in Economic Analysis *2018–2019*

Sciences Po Saint-Germain-En-Laye
Undergraduate Program *2014-2018*
Exchange year in the Department of Economics - National Taiwan University

Fellowships & Awards

La Caixa Fundation
Research Grant *2025*
Grant awarded for the project *The Bystander Issue* (34200€).

Cepremap - "Travail et Emploi" and "Eco Publique et Redistribution" programs
Research Grant *2025*
Grant awarded for the project *The Bystander Issue* (4200€).

BA/Leverhulme Small Research Grants
Research Grant *2024*
Grant awarded for the project *Social Media and Parenting* (9800£).

Discrimination and Diversity Workshop UEA
Honorary Mention *2023*
Mention for the presentation of the paper *The Role of Early Exposure to Technology in Women's STEM Choices*

CY Cergy Paris Université
Visiting Grant *2022*
Grant awarded for a 4 months research stay at Bocconi University in the AXA Gender Lab (2000€).

Conference

2025: LSE Department of Social Policy ISPP Seminar, Aix-Marseille School of Economics internal Seminar. *Forthcoming*: Afépop Conference, COSME Workshop Madrid, University of Barcelona Internal Seminar, Erasmus School of Economics External Seminar, INED internal seminar, 2nd Diversity and Human Capital Workshop Exeter, EQUINEQ Conference World Bank DC, Copenhagen Business School Seminar, PSE Applied Seminar.

2024: 3rd Gender and Economics Workshop - Luxembourg, Warwick/CAGE workshop on Gender and Inequality, AFSE Bordeaux, Workshop on Cultural Persistence and Transmission - Belfast, ESPE - Rotterdam, EEA - Rotterdam, Advances with Field Experiments Conference - London

2023: Alp-Pop La Thuile, JMA Strasbourg, AFSE Sciences Po Paris, CEP Work in Progress Education Seminar, Discrimination and Diversity Workshop UEA, EQUINEQ PhD Workshop, CEPR Paris symposium

2022: AFSE - DG Trésor Évaluation des Politiques Publiques, AXA Gender Lab Internal Seminar, SEHO London, ESPE Cosenza, Workshop in Gender and Education - Collegio Carlo Alberto, ESSEC Economics Department Brown Bag Seminar, THEMA Internal Applied Seminar

2021: EffEE PhD Workshop Berlin - WZB and ifo Center for the Economics of Education, GeFam Webinar - Family and Gender Economics Study Group, Workshop on Gender Inequality in Labour Markets - IAAEU, SEHO Boston - Poster, JMA Annecy - CREM START & TEPP, 2nd Brazilian Meeting in Family and Gender Economics, THEMA Internal Applied Seminar

2020: EEA Rotterdam

Referring

Education Economics, Journal of European Economic Association, Journal of Economic Inequality, Labour Economics, European Association of Young Economists (EAYE)

Teaching

Education Policy in Developing Countries
London School of Economics *2024-2025*

Understanding Policy Research
London School of Economics *2023-2025*

International Social and Public Policies
London School of Economics *2023-2025*

Education Policy, Reform and Financing
London School of Economics *2023-2025*

Foundations of Social Policy Research
London School of Economics *2023*

Economic Policies L2
Sciences Po Saint-Germain-En-Laye *2020-2022*

Macroeconomics L1, Microeconomics L2
CY Cergy Paris Université *2019-2020*

Position of Responsibility

WISPPRH initiative organizer
Department of Social Policy - LSE *2023-*

Webinar Gender and Family Economics co-organizer
CY Cergy Paris Université *2021-2023*

Graduate School elected representative
CY Cergy Paris Université *2021-2023*

Internal PhD Seminar co-organizer
CY Cergy Paris Université *2020-2022*

Research Visit

University of Barcelona
Hosted by Caroline Coly *June 2025*

Aix Marseille School of Economics
Hosted by Cecilia García Peñalosa *April 2025*

AXA Gender Lab - Bocconi University
Hosted by Paola Profeta *April - July 2022*

Language

Native: French

Fluent: English

Beginner: Italian, German

Software

Professional skills: Latex, STATA

Advanced Beginner: Python, R

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The Review of Economics and Statistics
MIT Press

Object: The Review of Economics and Statistics Fellowship for NBER Summer Institute

Dear Committee,

I am pleased to apply for the Review of Economics and Statistics Fellowship to attend the 2025 NBER Summer Institute. I defended my PhD in Economics at CY Cergy Paris Université in December 2023, and I am currently a second-year Fellow in the Department of Social Policy at the London School of Economics. My research examines how public policy and cultural beliefs shape inequality, with a particular focus on gender disparities. I strongly believe my profile aligns with the goals of this fellowship, and I am confident that this opportunity would both strengthen my academic trajectory and expand the reach of my work.

My research agenda aligns closely with the themes of the Summer Institute and with the Review of Economics and Statistics. It is structured around three pillars: (1) gender inequalities in science and technology, (2) parenting in the digital age, and (3) the role of technology in shaping beliefs and attitudes. The first pillar comprises two papers (one co-authored with Caroline Coly, University of Barcelona) addressing one of the key "pain points" of gender inequality in the 21st century, as identified by Bertrand (2020): gendered educational choices. The first paper investigates the role of early exposure to technology—particularly through gendered objects like computers distributed in the 2000s—and finds persistent effects on educational paths. This resonates with current concerns about gendered take-up of AI tools (Carvajal et al. 2025). The second paper explores the role of cultural values in explaining the "gender equality paradox" in STEM—where more gender-equal societies paradoxically display wider gender gaps in scientific fields.

The second pillar focuses on parenting and the digital environment. In a project co-authored with Greta Morando (University of Sheffield) and Sonkurt Sen (University of Bonn), we use a survey experiment to understand parenting practices in the age of social media and evaluate whether information treatments can promote safer and more constructive practices. The third and forthcoming pillar of my research investigates how social media influences belief formation compared to traditional media. Focusing on gender norms, this work investigates how specific features of social media—such as algorithmic curation, echo chambers, and addictive design—can shape beliefs and, in turn, drive behavioral change. Building on evidence from the political domain (e.g., Campante et al., 2023), I aim to explore whether similar mechanisms contribute to shifts in attitudes and norms related to gender.

My work would benefit greatly from attending the *Gender in the Economy*, *Economics of Education*, and *Children and Families* sessions. I aim to participate in all three, as they intersect with my three strands of my research. I would welcome the engagement with leading scholars working on related topics, introduce my research and receive feedback on my work. In addition, I believe that my

research also contributes a novel perspective to the conference—particularly through its focus on social media, which is emerging as a frontier topic in applied microeconomics. The Review of Economics and Statistics has already shown interest in this area (e.g., Armona, 2023), and my work further extends this line of inquiry by centering on the under-explored parent-child relationship, which intersects several domains including household economics, education, and digital economics. Exposure to diverse research at the Summer Institute would be instrumental in shaping the success of this agenda and hopefully lead to productive collaborations in the field.

The fellowship's objective is to broaden the range of researchers participating in the Summer Institute. I believe my background and trajectory make me a strong candidate in this respect. As a woman in economics—a field where gender disparities persist (Auriol et al., 2022)—visibility and exposure are key to building a more inclusive academic environment. Fellowships such as this one provide essential platforms for underrepresented voices. Furthermore, my academic path has not followed a traditional elite trajectory. I completed my PhD at CY Cergy Paris Université, where I finished top of my class in the research master, allowing me to earn a competitive three-year scholarship and benefited from excellent mentorship and. I made the most of the available opportunities, including a research visit to a top-tier institution, and have since secured a postdoctoral position at LSE. Yet I remain aware of how rare it is for scholars from non-elite institutions to access these networks. I believe these diverse experiences—and the perspectives they bring—are essential for enriching economic research. Finally, my current position in an interdisciplinary department grounded in social policy allows me to bridge economics with adjacent fields. As Angrist et al. (2020) observe, economics remains less outward-looking than disciplines like psychology and sociology, despite a positive trend toward greater openness. I am convinced that encouraging interdisciplinary dialogue not only in citing by also in network and conferences is key and will only strengthen the intellectual community of the Summer Institute.

In sum, my research addresses timely questions at the intersection of gender, technology, and social behavior—topics well aligned with several NBER Summer Institute sessions. My background, combining rigorous training at a non-elite institution with interdisciplinary experience at LSE, brings a distinct and underrepresented perspective to the Summer Institute. The RES Fellowship would allow me to refine my work, build valuable collaborations, and contribute to the broader goal of diversifying the conference.

References

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- Armona, L. (2023). Online Social Network Effects in Labor Markets: Evidence from Facebook's Entry to College Campuses. *Review of Economics and Statistics*, 1-47.

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Gendered Objects and STEM Choices: Evidence from France's Free-Computer Programs

Margaux Suteau *

May 2025

Abstract

This paper provides causal evidence that childhood exposure to technology influences preferences for gender-stereotypical educational fields. Using free computer programs in French middle schools (2001–2009) and a difference-in-differences approach, I find that exposure to gender-biased objects such as computers significantly impacts educational choices, particularly in math-intensive fields. Women experienced an 8% increase in math enrollment in high school and a 33% rise in higher education, driven by low-SES women. The effects on men are positive as well, but smaller. I discuss different mechanisms such as parental expectations, gender norms, skill development, and career prospects. Overall, this paper highlights the role of early socialization and access to gender-biased objects for reducing gender inequalities in education.

Keywords : Higher Education, Gender Gap, Technology, Public Policy.

JEL classification : I23, J16, I28.

*m.suteau@lse.ac.uk. Department of Social Policy, London School of Economics and Political Science, Houghton Street, London, WC2A 2AE, UK. The author thanks Massimo Anelli, Julien Bergeot, Oana Borcan, Olivier Donni, Fanny Landaud, Stefania Marcassa, Sandra McNally, Marion Monnet, Berkay Ozcan, Cecilia Penalosa-Garcia, Paola Profeta, Maddalena Ronchi, Almudena Sevilla. The author also thank participants and discussants in Alp-Pop La Thuile, JMA Strasbourg, AFSE Sciences Po Paris, CEP Work in Progress Education Seminar, Discrimination and Diversity Workshop UEA, EQUINEQ PhD Workshop, AFSE - DG Trésor Évaluation des Politiques Publiques, AXA Gender Lab Internal Seminar, SEHO London, ESPE Cosenza, Workshop in Gender and Education - Collegio Carlo Alberto, ESSEC Economics Department Brown Bag Seminar, THEMA Internal Applied Seminar, EffEE PhD Workshop Berlin - WZB and ifo Center for the Economics of Education and the Social Policy Quantitative Group in LSE participants. This paper uses confidential data from different data archive mainly maintained by the Quetelet-Progedo-Diffusion network. The data can be obtained by filing a request directly with the Quetelet-Progedo-Diffusion (available at this link). The rest of the data used in this article are available online and sources are in text. The author is willing to assist.

1 Introduction

The under-representation of women in STEM (Science, Technology, Engineering and Mathematics) fields, particularly those requiring math skills, persists as a significant challenge that partially explains the remaining gender wage gap (Breda et al., 2018; Bertrand, 2020). To understand the origins of differences in behaviors and preferences by gender, the psychology literature has proposed the gender schema theory, suggesting that from a young age, children rely on contextual cues to identify appropriate behaviors, activities, and objects for their gender (Bem, 1981; Bertrand, 2020). Aligning with this theory, economic studies have examined various environmental factors that transmit such contextual information and shape boys' and girls' beliefs and behaviors, including teacher biases (Lavy and Sand, 2018; Carlana, 2019; Mengel et al., 2019), role model influences (Breda et al., 2023), parental beliefs (Nicoletti et al., 2022), cultural norms (Nollenberger et al., 2016; Kahn and Ginther, 2017), skill development (Alan and Ertac, 2019) and so on.

This paper examines how exposure to objects associated with a certain gender, and especially technology, can influence students' choices of educational fields, focusing on girls' choice to enter scientific tracks. Indeed, the literature suggests that exposure to gender-biased objects like dolls can impact beliefs and preferences for certain careers by gender (Francis, 2010; Sherman and Zurbriggen, 2014; King et al., 2020), sparking a critical policy debate on the role of gender-neutral toys in reducing gender stereotypes from an early age (Russell, 2021; Kilander, 2024). [1] However, despite correlational evidence and a public debate, our understanding of the long-term causal effect of exposure to gender-biased objects on educational choices and labor market outcomes is limited. Indeed, isolating the effect is challenging due to environmental factors like parental influences (Coyle and Liben, 2016, 2020). Therefore, most existing research relies on qualitative or correlational analysis with small samples, examining reported preferences after brief exposure to gender-biased toys (Coyle and Liben, 2016, 2020; King et al., 2020). This study aims to provide causal evidence on the impact of childhood exposure to gender-biased objects on educational trajectories and career paths.

To this aim, this paper leverages public large-scale free-computer policy programs that provided universal access to personal computers for middle school students between 2001 and 2009 in specific areas of France and studies the effect on students' choices of fields in education. Technology exposure is relevant for three reasons to investigate the influence of gender-biased objects on educational choices, especially in gender-stereotypical fields like STEM. First, computers were engaging objects

1. I define gender-biased objects as objects associated with stereotypes about girls and boys' behaviors, preferences and attitude.

for teenagers during that period. Second, computers are strongly associated with male-dominated STEM careers like computer engineering or programming, and anecdotal evidence suggests early exposure is crucial for fostering vocations in the tech sector. [2] Third, the personal computers provided at the time had limited capabilities compared to today's smartphones and lacked networking features usually associated with female users, and were predominantly linked to activities perceived as more male-oriented, like gaming and programming. Therefore, the programs provide an exogenous shift in exposure to a plausibly gender-biased objects associated with building skills for male-dominated STEM education tracks.

The first part empirically verifies that patterns of computer access and use varied by gender, supporting the consideration of computers as a gender-biased objects during that period. Data from PISA 2000 shows that both girls and boys had equal access to a computer, girls exhibited a lower frequency of computer usage and reported lower confidence levels in usage. In addition, I show a positive and significant correlation between exposure to a computer at 15 and willingness to study and work in science broadly. This descriptive evidence corroborates qualitative findings of a gender gap in engagement with computers driving the long-term under-representation of women in math-intensive fields, despite similar exposure rates (Margolis and Fisher, 2002; Collet, 2004). Additionally, I find that socioeconomic status (SES) influenced heterogeneity in computer access and use : low-SES households were less likely to own a computer but used the resource more intensively when they had access. This sets the stage for important effects of the large-scale free-computer programs and potential heterogeneities by gender and SES.

In a second part, I examine the causal impact of large-scale free computer programs on the likelihood of students pursuing technology-oriented and scientific tracks in general in high school and in higher education. The programs provided a laptop computer to every middle school student in five *départements* (counties) for use in school and at home. [3] The programs were implemented at different times across counties. To analyze the program's causal effect, I employ a difference-in-differences approach using the timing and location of students' high school graduation to define treatment and control groups. I leverage administrative data on high school students and survey data from over 120,000 post-secondary students to identify those who were enrolled in a county with

2. Evidence from the 2019 and 2021 surveys by the startup CodinGame on a sample of 9000 workers in tech worldwide shows that a third of developers started coding before 14 years old. CodinGame is a platform for developers to improve skills and participate in recruitment contests. Survey results are available at Source.

3. A *département* is an intermediate level of government between the administrative *régions* and municipalities. Metropolitan France consists of ninety-six *départements*, with an additional five overseas classified as both overseas *régions* and *départements*.

a program after its implementation (treated group) and those who were enrolled before the program or in counties without it (control group). To account for potential heterogeneous treatment effects over time, I utilize the staggered difference-in-differences method by Callaway and Sant'Anna (2021) and verify that parallel trends hold.

This paper explores several critical educational decisions : 1) the choice of high school tracks after completing middle school, 2) the selection of fields of study within these tracks, and 3) the continuity of these track and field decisions into higher education. First, following the programs, students were more likely to choose vocational tracks in high school. This seems to be driven by students willing to specialize in scientific fields : for women, there is a significant 0.4 percentage point increase in enrollment in math-intensive fields compared to a 5% baseline. This effect is also observed for men, who increased by 4 percentage point (approximately 6%) their participation in math-intensive tracks. The programs had a lasting impact, significantly boosting women's participation in math-intensive subjects in higher education by 2 percentage points—a 33% increase from the baseline. Additionally, the programs led to a 3 percentage point rise in women's enrollment in vocational tracks in higher education, mirroring the shifts observed in high school tracks and demonstrating a clear progression into higher education pathways. For men, the program leads to a 6 percentage point increase (a 28% rise from the baseline) in participation in math-intensive tracks. In addition, I find that the programs did not affect the gender gap in high school, but slightly helped reducing the gender gap in higher education, as the increase for women in math-intensive fields is higher than for men in the treated group. Finally, the effects varied by socioeconomic status (SES) : low-SES women are driving the effect for math-intensive fields. There is no heterogeneous effects for men.

In addition to education choices, I use a survey of the French working population to assess the long-term programs effects. The effect on the labor market, measured by the share of individuals in math-intensive/computer science occupations or industries, the effect is slightly positive. The effect appears hard to interpret, however, as the programs seem to have increased mobility outside treated counties, in which case treated individuals cannot be identified.

I discuss potential mechanisms behind the shifts in educational choices using the choice model framework from Zafar (2012). First, I show that that there is no clear effects on academic performance, and while I cannot totally rule out this explanation, the main results suggest that this alone cannot explain the gendered effects, especially for women entering male-dominated fields. Second, I use the qualitative literature to discuss the hypothesis that the programs likely enhanced skill acquisition and enjoyment of technology-related coursework, fostering confidence and interest in these fields, es-

pecially among low-SES students with limited prior exposure (Perronnet, 2023; Fougère et al., 2021). Third, I examine the possibility that the programs signaled the value of tech-related tracks, and may have influenced parental expectations, encouraging children to pursue math-intensive programs. Finally, the programs may have shifted gender norms by countering stereotypes and expanding access to information, reducing stigma around girls' participation in tech and math fields and narrowing the gender gap (Bertrand et al., 2015; Folke and Rickne, 2020; Bursztyn et al., 2017, 2018; Bertrand, 2020).

Throughout the paper, I address several threats to the validity of the results to ensure their robustness. First, I tackle concerns about the identification strategy, particularly the non-randomness of treatment assignment. Counties may have self-selected into the programs based on characteristics that could influence the outcomes. To address this, I test the parallel trends assumption and confirm that the control and treated groups were also similar in levels before the intervention. Next, I account for potential confounders. I restrict the control group to counties with the same political affiliation as treated ones. I include controls for the supply of science-focused higher education institutions and the timing of broadband internet access in each county. I also test the robustness of the results by employing alternative estimation methods, including restricting the control group to geographically closer counties and testing the staggered difference-in-differences approach using a Two-Way Fixed-Effects methodology. Weighted and non-weighted results are compared to address potential endogenous sampling from the survey on post-secondary students. Finally, I perform two placebo tests, using alternative treatment timings and different sets of counties. These extensive robustness checks confirm the validity of the results.

This paper contributes to several strands of the literature. First, it adds a new mechanism to understanding the driver of inequalities through the reinforcement of stereotypical norms in childhood. As reviewed by Kahn and Ginther (2017), several environmental factors contribute to gender-biased choices in higher education : culture and inter-generational transmissions of norms and behaviors (Nollenberger et al., 2016) ; gender-biased teachers (Carlana, 2019) ; parental beliefs about their children's ability in different subjects (Nicoletti et al., 2022) ; class composition and peers' achievement (Landaud et al., 2020). This paper adds to this broad literature an under-studied and strong factor to the understanding of the gender gap in science, through the exposure to objects. While this mechanism is complementary to others, as gender-biased parents, peers or teachers might grant biased access to tools to their children for instance, I demonstrate that exposure can play an important role itself.

Efforts and policies aiming at bridging the gender gap in math have been extensively studied in the literature, with many encouraging examples. For instance, previous studies have highlighted the effectiveness of role model interventions (Breda et al., 2023; Porter and Serra, 2020), information-based interventions (Del Carpio and Guadalupe, 2022) or mentoring programs (Canaan et al., 2022; Canaan and Mouganie, 2023). In this paper, I study a universal program, non-targeted, and already implemented at a large scale, and show that better access to gender-biased objects can be complementary to exposure to role models or mentors. It suggests that such programs can complement individual-level interventions and be an effective policy tool for reducing gender inequalities in math-intensive fields.

Finally, this research paper contributes to the literature on the effect of computers and technology on children and teenagers. Most existing literature focuses on the effects on children's academic achievement or short-term outcomes, with mixed findings. The literature focus on two types of exposure : at school and at home. Studies tend to find negative or insignificant effects of computer allocation at school on academic achievement (Angrist and Lavy, 2002; Rouse and Krueger, 2004). The evidence on the impact of home computer ownership on student achievement is also mixed : Fairlie (2005) finds it increases the likelihood of school enrollment, and Fairlie et al. (2010) find an increase in high school graduation rates and decrease in suspensions/crimes. However, experimental studies show no significant effects of free computer programs on academic outcomes Malamud and Pop-Eleches (2011); Fairlie and Robinson (2013). In general, however, the literature highlights that early technology exposure increases computer skills (Malamud and Pop-Eleches, 2011; Bulman and Fairlie, 2016). This paper contributes by investigating the long-term impact on fields of study chosen in higher education and even before. The paper by Yanguas (2020) is the only other work studying post-secondary educational choices after a free computer program, finding no significant effect on the choice of tracks in Uruguay. This current paper uniquely focuses on gender differences, taking into account the biased baseline access to technology. It highlights how providing equal access to tools typically seized more by boys can influence girls' educational choices towards male-dominated fields like computer science and math-intensives tracks.

The rest of the paper is organized as follows : first, I present important institutional background information. In section 3, I show gender differences in technological use. Section 4 presents the data and section 5 the empirical strategy. The results section in 6 first presents findings for choices in higher education, followed but heterogeneity analysis and results once accounting for endogenous sampling. Robustness checks are provided at 7 and I discuss potential mechanisms in section 8.

2 Institutional Background

The following section presents the main features of the free computer programs and provides key background information on the scientific tracks available, the admission processes, and other institutional features of the French educational system.

2.1 The Free Computer Programs

The five free computer programs were introduced in the early 2000s, between 2001 and 2009. The first program was launched in 2001 in the county of Landes and was extended to all students enrolled in 9th grade (middle school) in 2002. In 2003, Bouches-du-Rhône implemented a similar policy, Ordina 13, followed in 2004 by Ille-et-Vilaine. Four years later, two additional programs were introduced : first in Oise in 2009, and then in Corrèze later the same year. For a graphical overview of the timeline, see Figure A1. [4] For a map of the counties, see Figure 1. These programs were implemented autonomously by the counties' authorities with several objectives : bridging the digital gap, providing students with the necessary skills for the labor market, and fostering new pedagogical practices (Khaneboubi, 2009).

Table 1 – Characteristics of the Free-Computer Programs

	Landes	**Bouche-du-Rhone**	**Ille-et-Vilaine**	**Correze**	**Oise**
Start Date	2002	2003	2004	2009	2009
End Date	On-going	2016	No Source	On-going	2016
Name	.	*Ordina13*	*Ordi35*	*Ordicollege19*	*Ordi60*
Equipment	Laptops	Laptops	Laptops	Laptops then Tablets	Laptops
Donation Type	Lent	Lent and Given for small fee	Lent	Lent and Given for small fee	Given
Home	Yes	Yes	Yes	Yes	Yes
School	Yes	Yes	Yes	Yes	No
N Students First Cohort	2753	19739	10472	2559	8748

Notes : Characteristics of the free-computers programs. Most information are from Khaneboubi (2009) and institutional reports (Inspection Générale de l'Education Nationale, 2011, 2012). Information about the end of the programs are gathered from various press article : see Bouche-du-Rhone, Landes, Oise. *Home* means that the students were able to take the computer home, *School*, that they were allowed to take it home.

4. Additionally, Table A1 provides a more detailed timeline by county. In particular, it highlights the initial or "test" year of the programs, during which only a few classes or schools received computers. These "test" years are not included in the estimations.

Despite being independently launched, the five programs shared key characteristics, summarized in Table 1. The most notable was the provision of a laptop computer to every student for autonomous home use. These laptops included open-source software, online textbooks, spreadsheets, word processors, and encyclopedias, enabling access to resources for both independent study and classroom activities. Table 1 also highlights implementation differences across counties. In some counties, laptops had to be returned after middle school, while in others, families had the option to purchase them. Equipment types also varied : some counties made substantial investments in school computer infrastructure, such as interactive boards and dedicated rooms, while others focused solely on home use. One county even switched to using tablets partway through the program. Finally, I have no records of messaging or information given to students who benefited from the programs alongside the computer, neither from teachers, schools or the county authorities.

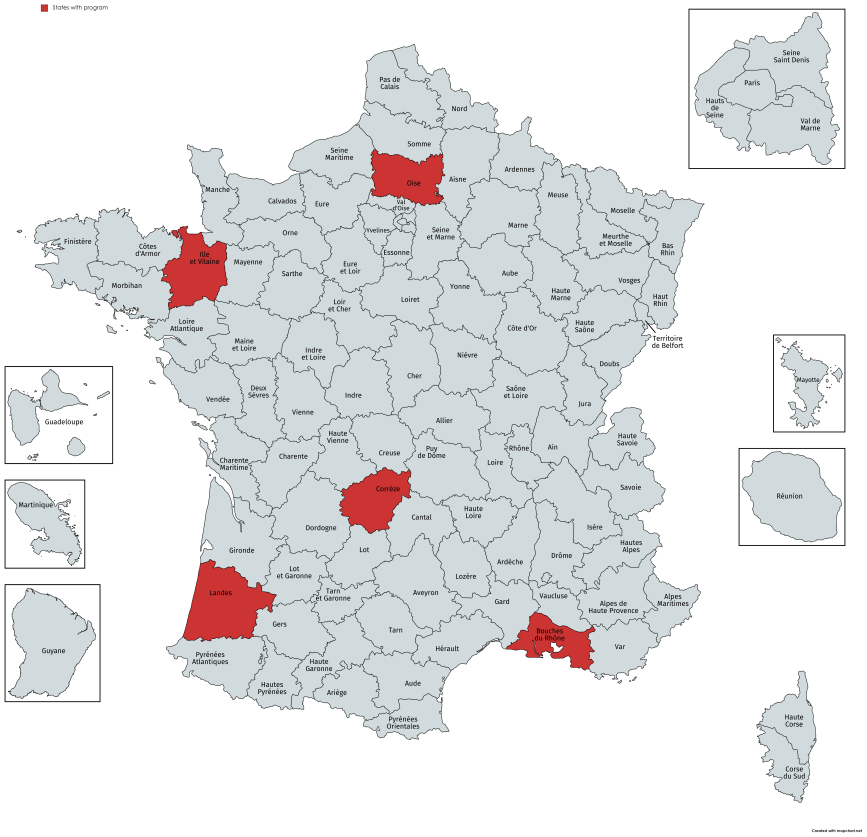
While these variations may have influenced outcomes, there were too many minor differences to allow for a thorough heterogeneity analysis. One major difference accounted for is timing : the first three programs were launched in the early 2000s, whereas the last two were implemented in the late 2000s. Given the rapid technological advancements during this period, the impacts of these two groups likely differed. Tthis is discussed further in the robustness checks section.

According to qualitative research, computer use in classrooms remained limited even after these programs were implemented (Khaneboubi, 2009). Teachers did not significantly change their teaching practices in core subjects like mathematics or language. However, computers were more easily integrated into technology-intensive subjects such as music and art. The likely explanation for this is the lack of ICT (Information and Communication Technology) training for teachers at the national level. Data shows that only 18% of teachers who were likely teaching when the programs started had received even "some" ICT training during their teacher education (DEPP, 2021). This suggests that classroom technology use was mostly limited to a few experienced teachers and that most students' exposure to computers occurred at home.

While reports and qualitative studies suggest that all students benefited from these programs, a few potential issues could challenge this assumption. For instance, technical problems or equipment shortages may have prevented some schools from distributing laptops. However, no evidence of such problems has been identified, and any such issues would likely have affected very few students, as a significant supply issue would probably have been reported. In Corrèze, Bouches-du-Rhône, Oise, and Ille-et-Vilaine, official reports and press articles indicate that both public and private schools

were equipped. In Landes, the first program, only public schools participated. [5] However, in Landes, 89.4% of students were enrolled in public schools in 2007. Since the vast majority attended public schools, this limitation should not bias the estimates. [6]

Figure 1 – Maps of Treated Counties



Notes : The map shows the treated counties group, in red, and the control counties group, in gray. In most specifications, I use all other counties as the control group, in the robustness checks section, I also restrict the control group to only neighboring counties as well as counties with the same political leaning.

An important question regarding these programs is their effect on actual computer ownership among children. To address this, I use survey data from the *Panel de la DEPP*, which tracks students from middle school to high school. The key variable for this analysis is the following question : "Does your child own their own computer ?" My analysis focuses on the 2007 cohort, tracking students from

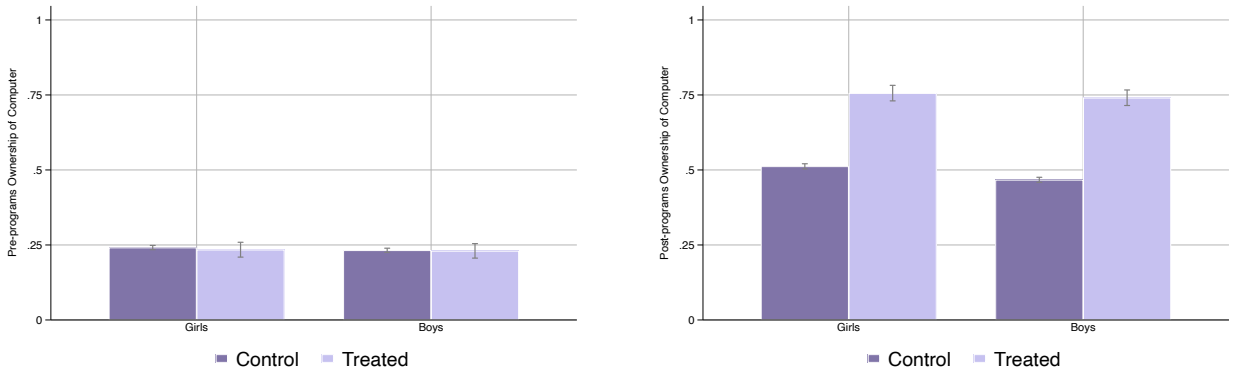
5. For Bouches-du-Rhône : *Trassard M. 2007. Un ordinateur portable pour les collégiens des Bouches-du-Rhône.* Article. For Oise : *2008. Le coût d'Ordi 60 fait tousser la droite. Le Parisien.* Article. For Ille-et-Vilaine : *du Guerny S. 2004. L'Ille-et-Vilaine informatise tous les élèves de troisième. Le Parisien.* Article. Official reports : *Inspection générale de l'éducation nationale. 2012. Le plan «Un collégien, un ordinateur portable» dans le département des Landes. Rapport n° 2012-148.* and *Inspection générale de l'éducation nationale. 2011. Le plan Ordicollège dans le département de la Corrèze. Rapport n° 2011-112.*

6. *RERS 2008 (Repères et références statistiques).*

their first year of middle school (2007) to high school (2011). This allows for a comparison between students in counties that implemented a free-computer program (treated group) and those that did not (control group), both before and after the programs were introduced.

Figure 2 shows that in 2007, prior to the implementation of these programs, there was no significant difference in computer ownership between the treated and control groups. By 2011, however, students in counties with the program were 27 percentage points more likely to own a computer compared to the control group. This effect was slightly larger for boys than for girls, but the gender difference is not statistically significant, providing no evidence of gender bias in the distribution of free computers.

Figure 2 – Ownership of a Personal Computer Pre and Post Treatment



(a) Pre-Programs **(b)** Post-Programs

Notes : Share of children owning a personal computer using the *Panel de la DEPP* wave 2007 and 2011. The outcome is a dummy equal to one if the parent answered yes to the question "*Does your child own their own computer*" in 2007 (pre-programs) or in 2011 (post-programs).

It is worth noting that other counties also implemented similar policies or programs, but these are not directly comparable due to differences in timing and implementation. For example, in 2012, Val-de-Marne county provided personal laptops and internet access to 6th grade students for school use. However, by this time, household technology access in France had significantly improved since the early 2000s, making it likely that students already had access to such technology at home. This makes it difficult to draw meaningful comparisons with earlier programs. Furthermore, the qualitative literature and institutional reports primarily reference these five programs due to their similarities in timing, scale, and implementation (Khaneboubi, 2013). [7]

7. Additionally, some counties or states offered financial aid to students from disadvantaged families, with the amount of aid ranging from €20 to €200 based on parental income. Examples include Midi-Pyrénées and Pays-de-la-Loire : see *Ph. R. 2010. Toulouse. Midi-Pyrénées. Un ordinateur pour chaque lycéen. La Dépêche.* Article, and *2013.*

2.2 The French Educational System

This section provides background information on the French educational system, covering both high school (*Lycée*) and higher education.

After completing middle school, students enter high school, where they can choose from three main paths :

1. Academic (*Général*) : This path is academically demanding and designed to prepare students for higher education.
2. Technological (*Technologique*) : This path offers both career opportunities and access to higher education, though not the most selective tracks.
3. Vocational (*Professionnel*) : This path focuses on preparing students for direct entry into the labor market.

As shown in Figure A2, students in the academic track can choose between academic and technological specializations after completing a common first year. The vocational track is further divided into two sub-paths : one leading to a Baccalaureate degree (*Baccalauréat*), which qualifies students to pursue higher education, and another focused solely on preparing students for the labor market. Students in the latter path would need to obtain an additional qualification to access higher education. Within each track, students can specialize in a wide range of subjects, including sciences, humanities, social sciences, or specific fields such as computer science, electronics, or tourism.

Upon passing the Baccalaureate, high school graduates can pursue higher education in various types of institutions, depending on their high school specialization :

— Public universities : These institutions are tuition-free and non-selective, offering access to a broad range of fields.

— Technical or vocational institutions (*IUT* or Advanced Vocational Programs (*BTS*)) : These are two-year programs combining vocational training and coursework.

— *Grandes Écoles* : These selective schools (public or private) are highly competitive and often charge significant tuition fees.

— *CPGE (Classes Préparatoires aux Grandes Écoles)* : High-achieving students can opt for these two-year intensive preparatory programs, which lead to selective business or engineering *Grandes Écoles*.

Ordipass : 5,000 ordinateurs distribués aux lycéens et apprentis des Pays de la Loire. IT Pro News. Article. However, requiring families to actively request a computer represents a different approach, as it could still impose a financial burden on disadvantaged households. This system may also suffer from gender imbalances if boys are more likely than girls to request the computers.

This paper examines several key educational choices : 1) The selection of high school tracks following middle school, 2) The fields of study chosen within these tracks, 3) Whether these track and field choices persist into higher education.

3 Exclusion of Girls from Technology : An Analysis of the Gender Gap in Computer Use

Before analyzing the causal effect of early computer exposure on higher education choices, this paper first examines the initial gender gap in computer access and use. It explores how boys and girls use technology differently and investigates whether a gender gap exists in access to and use of computers. Furthermore, it examines the link between this gap in computer use and the willingness to study sciences.

Qualitative evidence highlights that social norms create barriers for girls in accessing and using technology, contributing to their exclusion from this domain. Studies in France have shown how these barriers reinforce gendered differences in technology use among children (Margolis and Fisher, 2002; Collet, 2004). For instance, Collet (2004) conducted interviews with 17 individuals working in the IT sector and found that the introduction of personal computers in households reinforced a predominantly masculine image of the computer scientist, effectively sidelining girls. The study links this exclusion to the under-representation of women in STEM education and occupations. Similarly, in a study of 45 female high school students, Perronnet (2023) found that girls who participated in programming during their leisure time—a small minority—were significantly more likely to express interest in careers not only in computer science but also in broader engineering disciplines. This early exclusion has far-reaching implications : only girls who overcome these barriers and engage with technology seem more likely to pursue scientific fields.

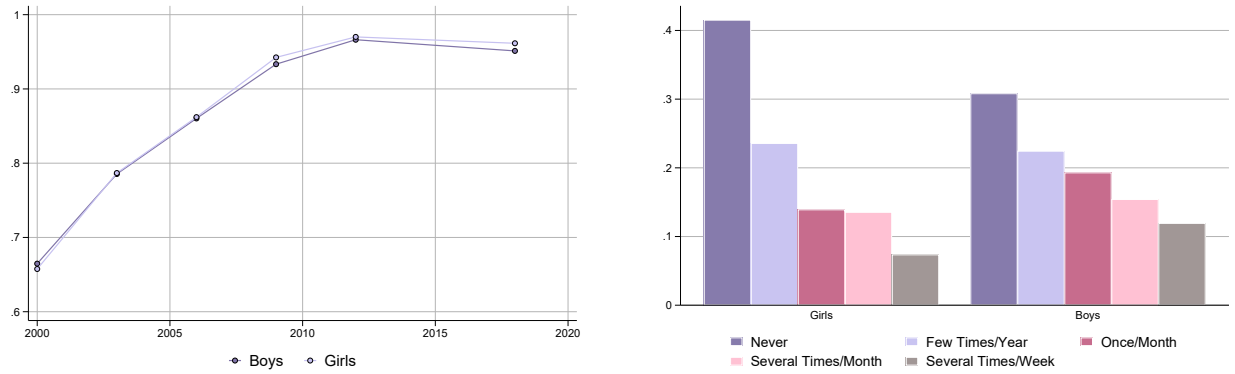
To complement the qualitative literature, I quantitatively investigate these patterns using PISA 2000 data, focusing on children aged 14–16 in France, the age at which students received computers from the programs. The analysis examines data on ICT ownership, use, and confidence reported by children. Figures 3a and 3b reveal that while both genders have similar access to computers, girls tend to use them less. In the French PISA 2000 sample, 30% of boys reported never using a computer, compared to 40% of girls. Conversely, 12% of boys reported using a computer multiple times per week, compared to only 8% of girls. [8] Furthermore, Figure A3 shows that girls feel less

8. Patterns of ICT ownership are similar when using data on computer and internet access from the *Enquête sur les technologies de l'information et de la communication*. Figure A4 shows that more than half of households with

competent than boys in computer use across countries, with predominantly negative or lower average Weighted Likelihood Estimates (WLE) scores for girls compared to boys. [9]

How can we interpret these patterns ? Gender schema theory offers an interesting framework. Children's perceptions of what behaviors, activities, and objects are appropriate for their gender are shaped by societal and familial influences. This may make boys more likely to use computers in response to societal or parental expectations, while girls may be discouraged from doing so (Bem, 1981; Margolis and Fisher, 2002; Collet, 2004). This dynamic is particularly pronounced in households where resources must be shared. For instance, in early 2000s France, the *Enquête sur les technologies de l'information et de la communication* shows that most households owned only one computer : in 2005, 76% of households owned only one fixed computer, and only 24% owned non-fixed computers or laptops. The qualitative evidence cited above also suggests that, in such contexts, boys were more likely to be the primary beneficiaries of technology, further discouraging girls from using it (Margolis and Fisher, 2002; Collet, 2004).

Figure 3 – Ownership and Frequency of Use of a Computer



(a) Ownership of computer

(b) Frequency of Computer Use

Notes : Data from the PISA 2000 survey. Data are downloaded in STATA format from : Jakubowski and Pokropek (2013). The question used in 3a is the self-reported availability of a computer at home : 1 being not owning a computer, and 2 being ownership. For subgraph 3b, I use the question *3How frequently do you use a computer3*, where students can answer Never, Few Times per Year, Once a Month, Several Times/Months, and Several/Week.

The PISA data also allows for an examination of how socioeconomic status (SES), alongside gender, contributes to the digital divide. I use parents' highest occupational status as defined in the PISA data and create quartile. Figure A7 illustrates a significant gap in computer ownership

children had a computer in 2000.

9. Statistics for France are unavailable, but trends in nearby countries suggest that France is not an outlier. Figures A3, A5, and A6 indicate similar patterns between France and neighboring countries regarding technology access and use, as shown in PISA, Eurostat, and the *Enquête sur les technologies de l'information et de la communication.*

in 2000 : only 75% of children from the lowest SES quartile owned a computer, compared to 95% of children from the highest SES quartile, highlighting disparities in access to resources. However, among computer owners, the pattern reverses when considering usage. Only 30% of children from the lowest SES quartile reported never using a computer, while over 40% of those from the highest SES quartile did so. This suggests that while higher SES children had greater access to computers, they used them less frequently. One possible explanation is that higher SES children benefited from greater parental involvement stricter rules and structured digital learning activities. These trends will be considered in analyzing how the programs might have heterogeneous effects by SES.

Next, I use data from the 2006 wave of PISA to explore the relationship between computer ownership and students' willingness to pursue scientific education and careers. Specifically, I regress computer ownership on responses to the following statements about future aspirations in science : *I would like to work in a career involving broad science*, *I would like to study broad science after secondary school*, *I would like to spend my life doing advanced broad science* and *I would like to work on broad science projects as an adult* controlling for the parents occupation and education, if they have a desk, a room of their own, a place to study and a dictionary at home. The results, presented in Table A2, reveal a significant positive correlation between computer ownership and a general willingness to study science, highlighting the potential of computer access to foster interest in science-related fields. Additionally, computer ownership and boys' aspirations to pursue advanced broad science tracks and engage in scientific projects in the future. For girls, the correlation between computer ownership and pursuing scientific tracks is positive, but not statistically significant. This suggests that a link between exposure to computers—a tool deeply embedded in the "scientific culture"— and long-term preferences for science.

4 Data

We now turn to the causal analysis of the medium- and long-term effects of early exposure to technology through the educational programs.

High School - First, I examine the impact of these programs on students' high school choices immediately following middle school and their exposure to the intervention. To measure this effect, I utilize administrative data *Base Centrale Scolarité* (BCS), which tracks students from primary school through high school graduation between 2004 and 2015. Provided by the French Ministry of Education, this dataset includes detailed information on students' academic tracks, age, and parental socio-economic status throughout their education. A major strength of the BCS data lies in

its comprehensiveness, enabling an analysis of students' choices among academic, technological, and vocational tracks, as well as their specializations within these tracks. Furthermore, I can study these educational choices at three key stages of high school : 10th grade (*Seconde*), 11th grade (*Première*), and 12th grade (*Terminale*). To conduct this analysis, I compile all available waves of the BCS data, creating repeated cross-sectional samples for each grade and year. This approach ensures a year-by-year tracking of educational choices. However, the BCS data's limited historical depth means that the first program implemented in Landes is excluded from the analysis, as pre-treatment cohorts are unavailable ; the first beneficiaries of this program entered high school in 2003.

Higher Education - Next, I investigate whether the program's effects in high school extended to influence students' pursuit of scientific tracks in higher education. This analysis requires data that is representative of post-secondary students across diverse fields and institutions in France. For this purpose, I use the *Conditions de la Vie Étudiante* (CVE) survey from the *Observatoire de la Vie Étudiante* (OVE). [10] To construct the dataset, I merge all survey waves from 1994 to 2016, yielding a repeated cross-sectional sample of 125,747 individuals. This sample is restricted to individuals aged 17–35 who graduated from high school in metropolitan France between 2000 and 2015 and were enrolled in initial training. [11] The final cohort included in the survey graduated in 2015, as no subsequent data is available.

While the OVE survey offers rich insights, it has limitations, including a smaller sample size and its status as secondary data. The alternative, the *Système d'information sur le suivi des étudiants* (SISE) administrative data on all students in French higher education, also has drawbacks. Notably, its publicly available version excludes students in private institutions—a significant limitation given that private engineering schools are key pathways for science-focused students. Moreover, comprehensive data collection for private institutions only began in 2011, particularly for engineering schools. [12]

Despite its limitations, the OVE survey has several strengths. Conducted every three years since 1994, it provides historical depth and captures students from a wide range of higher education institutions, including public universities, high school-affiliated programs, engineering schools, busi-

10. Data provided by Réseau Quetelet Progedo : for higher educatinon, Conditions de vie des étudiants (CdV) - Fichier historique - 1994-2006 (2006, OVE), 2010 (2010, OVE), 2013 (2013, OVE), and 2016 (2016, OVE), and for high school Base centrale scolarité (BCS) - 2004-2015, DEPP - Ministère de l'éducation nationale (producteur), ADISP (diffuseur).

11. In France, individuals sometimes enroll in higher education after time spent in the labor market, either for career advancement or reorientation. This includes both part-time training while employed and full-time enrollment after leaving the workforce.

12. Access to this more comprehensive data is also restricted, especially for researchers outside of France.

ness schools, and institutions under the Ministry of Culture and Communication. For instance, the 2016 wave had responses from 46,340 students, representing 84% of the French higher education population, with a 20% response rate.

One potential concern with the OVE survey is selection bias, especially an over-representation of students from treated regions. For example, students with better access to computers through the programs may have been more likely to participate in the survey, particularly as the last three waves were collected online. To address this issue, I weight the results using the weights provided by OVE administrators, following the methodology of Solon et al. (2015) for adjustment to endogenous sampling. These weights, based on administrative data from the Ministry of Education, adjust for differences in gender and age distributions. I also present unweighted results in the robustness checks section, discussing the implications of potential sampling biases, as recommended by Solon et al. (2015).

In addition, this paper utilizes several additional datasets to supplement the OVE and the BCS. The primary characteristics of these additional datasets are summarized in Table A3.

Individual Level : First, I use one administrative dataset and one survey, both at the individual level.

Recensement de la population (Population census) : I use the population census data, containing selected information from censuses carried out every year since 1968. It includes the population residing in mainland France and provides individuals' characteristics localized at the county level. I use the Population Census to assess differences in demographic characteristics between counties with a program and those without.

Enquête Emploi (EE) : Conducted by the Ministry of Labor since 1950, the EE is a key source for analyzing workforce structure, unemployment trends, and labor market dynamics in metropolitan France. It surveys a representative sample of individuals aged 15 and over from ordinary households. I use the EE to assess the long-term labor market effects of the programs, focusing on occupations and industries in the treated counties. The dataset provides detailed occupational information, and includes firm-level data on location and industry type, enabling the calculation of gender representation in male-dominated occupations in tech or science-related industries by county and year.

County Level : Various crucial pieces of county-level information are employed for robustness checks.

Success of Graduation Exam : I gather data on the success of high school graduation exams at the county level between 2000 and 2016, along with county-level unemployment rates for the same period. This information, provided by the Ministry of Education, allows me to assess the potential effect of the programs on high school graduation outcomes.

Unemployment : I use county-level unemployment rates for the period 2000 and 2016 provided by INSEE to check the difference in pre-programs labor market characteristics.

Internet Access : To evaluate the impact of internet access in the counties, I use broadband access data in France from Malgouyres et al. (2021). The dataset spans the years 2000 to 2007.

Higher Education Institutions : Finally, I use administrative data available through the Ministry of Higher Education Open Data, which provides a list of all higher education institutions in France. I complement this with hand-collected data on post-secondary institutions offering degrees in computer science, to assess the effect of local insitution on the technological environment. This information allows me to evaluate the potential confounding effects of higher education supply in the treated counties. Both data sources were collected from public sources in 2022.

4.1 Descriptive Statistics

Descriptive statistics at the individual level, presented in Table A4, are derived from the BCS and OVE data, capturing individual characteristics of students in my sample in high school and higher education. As many women are enrolled in high school as men according to the BCS, while the OVE sample consists of 36% men and 64% women, reflecting the usual gender bias in survey responses. Age distribution aligns with expected educational stages, with students averaging 15 years old in the first year of high school and 18 years old in the final year. Parental socio-professional categories (CSP) are classified into four main groups, ranging from Very High SES (e.g., executives, engineers) to Low SES (e.g., blue-collar workers). For simplicity, I report only these two main categories in the table. The BCS records the household head's CSP, typically the father, while the OVE collects data on both parents' professions. The BCS shows that 21% of high school students come from very high SES households and 23% from low SES backgrounds. In contrast, the OVE reveals a higher proportion of very high SES students and fewer from low SES households in higher education, reflecting the over-representation of high SES students in higher education.

Next, I summarize how students are distributed across tracks in the French system in Table

A5, following Figure A2. In the first year of high school (known as *Seconde*), most students opt for the general academic track, which prepares them for higher education. About 63% of male students and 72% of female students choose this path. The remaining students are divided between vocational tracks, with a Baccalaureate degree and without. Male students are more likely to enroll in vocational tracks (28% in vocational - Baccalaureate and 21% in vocational - Non-Baccalaureate) throughout their three years of high school. In the second and third years of high school (*Première* and *Terminale*), students can also enter a technological track, which offers a middle ground between the academic and vocational tracks. By the second year, 16% of boys and 18% of girls are enrolled in this track. Table A6 shows descriptive statistics for the different academic tracks : most students are enrolled in the scientific specialization.

Table 2 presents descriptive statistics for students' field choices. Given that the programs focus on exposure to computers, I first analyze the effect on fields related to computing. The category *Computer Science* is defined to measure the impact on technology-related fields. Additionally, I divide science fields into two subgroups : *Math-Intensive Tracks*, which include subjects such as mathematics, computer science, technology, construction, and mechanics, and *Unbiased Science Tracks*, which cover subjects like biology, earth science, and agriculture. This distinction is based on evidence that women are particularly under-represented in the former, while increasingly present in the later (Kahn and Ginther, 2017). In high school, only a very small percentage of both boys and girls are enrolled in computer science-related fields, as these specializations are rarely offered at this level. However, 64% of boys in vocational tracks specialize in math-intensive subjects, compared to only 4% of girls. Both boys and girls have limited enrollment (2-4%) in unbiased scientific fields.

Using the OVE data, I provide further descriptive statistics on students' choices of fields and types of institutions in higher education in Table A7. The OVE categorizes fields into seven broad areas : humanities, social sciences, natural sciences, economics and business, law, health, and education. In higher education, the gender divide persists : 7-8% of men pursue degrees in computer science, compared to only 2% of women. Similarly, 24% of men and 7% of women are enrolled in math-intensive fields. For unbiased science fields, the gender gap is smaller, with both men and women participating at rates of 6-7%. [13] Consistent with prior research on gender differences in academic preferences, male and female students show similar enrollment rates in fields like economics, business,

13. To note that I use the same terminology throughout the paper for both high school specialization and higher education fields of study, to avoid confusion. However, they do not have the same meaning : in high school, math-intensive tracks are mainly vocational, while in higher education, they can be highly selective, competitive, and academically challenging.

Table 2 – Descriptive Statistics for Educational Choices Variables in Secondary and Post-secondary Education

	Treated				Control			
	Men		Women		Men		Women	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
High School 1st Year								
Computer Science	0.00	0.02	0.00	0.00	0.00	0.01	0.00	0.00
Math-Intensive	0.62	0.49	0.04	0.20	0.63	0.48	0.05	0.21
Unbiased Science	0.05	0.22	0.05	0.21	0.05	0.22	0.05	0.21
N	128920		97991		1646263		1274243	
High School 2nd Year								
Computer Science	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Math-Intensive	0.63	0.48	0.04	0.20	0.63	0.48	0.04	0.20
Unbiased Science	0.04	0.21	0.04	0.19	0.04	0.19	0.03	0.18
N	156653		123021		2037197		1629251	
High School 3rd Year								
Computer Science	0.00	0.01	0.00	0.02	0.00	0.01	0.00	0.00
Math-Intensive	0.64	0.48	0.02	0.15	0.62	0.48	0.04	0.20
Unbiased Science	0.04	0.18	0.02	0.15	0.03	0.17	0.02	0.14
N	62031		47159		837471		635772	
Higher Education								
Math-Intensive	0.19	0.39	0.06	0.24	0.21	0.41	0.06	0.25
Unbiased Science	0.06	0.24	0.07	0.26	0.06	0.25	0.08	0.27
N	2804		5222		41826		75895	

Notes : Descriptive statistics for educational choices variables using the Base Centrale Scolarité dataset, which contains information on high school students in France and the OVE data set historic dataset, 2010, 2013, and 2016, restricted to students between 17 and 35 years old, who graduated in metropolitan France, and who are enrolled in initial training.

and health. However, more males tend to pursue scientific disciplines, while more females enroll in humanities programs. Regarding higher education institutions, France has several types, each offering different diplomas in the same fields, as described in section 2.2 and in Figure A2. Male students are overrepresented in scientific institutions such as engineering schools, though most students, regardless of gender, are enrolled in public universities.

5 Empirical strategy

To determine the effect of the programs, I use a difference-in-differences approach, exploiting the timing of implementation between counties as a quasi-natural experiment to identify the causal effect of such exposure on medium and long-term choices in education. A naive estimation of the effect would look like :

$$Y_i = \alpha_t + \omega_c + \beta_1 Treated_i + \beta_x X_i + \epsilon_i \tag{1}$$

Where Y_i is a dummy variable equal to one for being enrolled in a particular field of study in higher education, α_t is the time-fixed effect, proxied here by the year of high school graduation, and ω_c is the county-fixed effect. $Treated_i$ is a dummy equal to one for students who studied in Landes, Bouches-du-Rhône, Ille-et-Vilaine, Oise, and Corrèze after the implementation of the programs. For the analysis of high school choice, I use county and year of enrollment for a given year, and for higher education the year and county of high school graduation as a proxy for the year and county at the time of the programs.[14] X_i are covariates : first, parents' socio-professional background (a proxy for socio-economic status - SES) because I showed in section 3 that SES does matter in explaining exposure and use pre-programs, and second, age, to control for students who repeated or skipped a grade.[15]

In this paper, I move beyond the naive specification to incorporate new developments in the Difference-in-Differences (DD) approach for staggered treatments. Recent literature argues that the classic DD assumption of treatment stability over time does not hold in staggered treatments (Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021). This is particularly relevant here, as the rapid spread of ICT in France during the 2000s means students who benefited from the programs earlier (in Landes, Bouche-du-Rhône, and Ille-Et-Vilaine)

14. The mechanism is clarified in Figure A1 : for instance in Landes, the policy was launched in the 2002-2003 academic year and first targeted 9th and 8th graders. According to the French system, most of these students graduated during the 2005-2006 academic year. The year of treatment for Landes is 2006 since the first students who obtained computers passed the graduation exam in 2006.

15. According to PISA 2012, 28.4% of students aged 15 have already repeated a grade (Source).

might have been affected differently than those in later programs. Callaway and Sant'Anna (2021)'s approach allows me to address concerns about varying treatment effects over time and identify the causal effect of ICT exposure on educational choices.

I estimate the average treatment effect ($ATT_{g,t}$) for each group g at a period k following Callaway and Sant'Anna (2021). I choose to use the never-treated group as the counterfactual (as opposed to not-yet-treated). This choice is motivated by the characteristics of the control group used here : the never-treated group is large enough, available, and relatively similar to the treated group (see Table 2). [16] Finally, their estimator allows me to calculate different aggregated estimates. This will be particularly helpful in this setting : indeed, the authors suggest that in the case of a small number of observations per unit, aggregated group-time average treatment effects are less likely to be biased. I follow the authors' suggestion and use the aggregated results. The results are clustered at the county level. [17]

One concern is the potential non-randomness of the treatment, as counties self-selected into the programs, which were implemented at the county level using their own funds. This raises the possibility that pre-existing conditions influenced their decision to adopt the initiative—for instance, treated counties may have already had characteristics that encouraged women's participation in scientific fields. However, it is important to note that the programs were not part of a coordinated national agenda but rather implemented independently by counties. While self-selection remains a challenge, the absence of a centralized strategy to target specific counties—whether those lagging behind or exhibiting promising conditions—suggests that the decision to adopt the program may have been driven by local political dynamics rather than systematic targeting. This provides some support for the hypothesis of randomness, though concerns about self-selection persist.

Therefore, in the results section, I graphically show that the parallel trend assumption is plausible, ruling out the possibility that the treated and control units have followed a different trend over time before treatment. [18] I also conduct an empirical analysis comparing various educational, economic, and technological characteristics between the two groups to show that not only counties followed the same trends pre-programs, but were also on average similar in levels. The results, presented in Table A10, indicate no significant differences in educational characteristics at the individual

16. I test the results using the not-yet-treated control group, and I find the same results (Tables A8 and A9 in the Appendix)

17. I also use the *doubly robust improved* estimator as recommended by Callaway and Sant'Anna (2021) for its robust features against model mispecifications compared to other options.

18. As Callaway and Sant'Anna (2021) note, potential covariate-specific trends can result in important biases. Therefore, I take this potential issue into account and report pre-trends with covariates.

level or county level pre-programs : the groups were similar in terms of age in higher education and enrollment in math-intensive or less biased scientific tracks as well as in high school graduation exam enrollment and success rates. Technological access rates, including computer and internet access, were also comparable. Economic characteristics, analyzed using census data, showed some significant but small and inconsistent differences, with no clear pattern (Treated counties had both larger shares of individuals with no diploma and with higher education degrees and higher proportions of both low and high socioeconomic-status individuals compared to the control group).

Finally, in the robustness check section, I include various robustness checks to rule out several additional plausible confounding effects : the role of broadband internet, the supply of higher education institutions and the political environment of the county at the time. I show that these potential additions do not affect my results.

6 Results - Unbiased Exposure's Impact in Education Decision

In this section, I study how exogenous exposure to computers affects choices in higher education.

6.1 High School Choices

I analyze whether the programs impacted students' choices between academic and vocational high school tracks. Table 3 shows a small but significant shift from academic to vocational tracks for both genders, though the results for women depend on whether covariates are included. Women are 0.3 percentage points (pp) less likely to choose an academic track (a 0.4% drop compared to the baseline control mean) and 3% more likely to choose a vocational track without a Baccalaureate degree. On the other hand, men are 0.05 pp less likely (a 0.8% drop) to choose the academic track and 1pp less likely to choose a vocational Baccalaureate track, and 7% more likely to choose a vocational track without a Baccalaureate degree.In their second and third year of high school (Table A11), treated students are more likely to move into technological tracks. For clarity, I focus on the first year's choices, which lay the groundwork for later decisions. Overall, the results indicate a consistent trend : students are moving away from academic tracks toward technological and vocational ones.

This leads to the second question : did these programs encourage students to specialize sooner, potentially aiming for a more direct path into the workforce, to study scientific tracks ? Table 3 presents results that generally validate the hypothesis, showing a shift toward scientific fields. While there is no significant effect of the program on enrollment in computer science tracks, likely due to their limited availability at the high school level, there is a significant and large positive effect

Table 3 – ATT - Educational Choice in High School

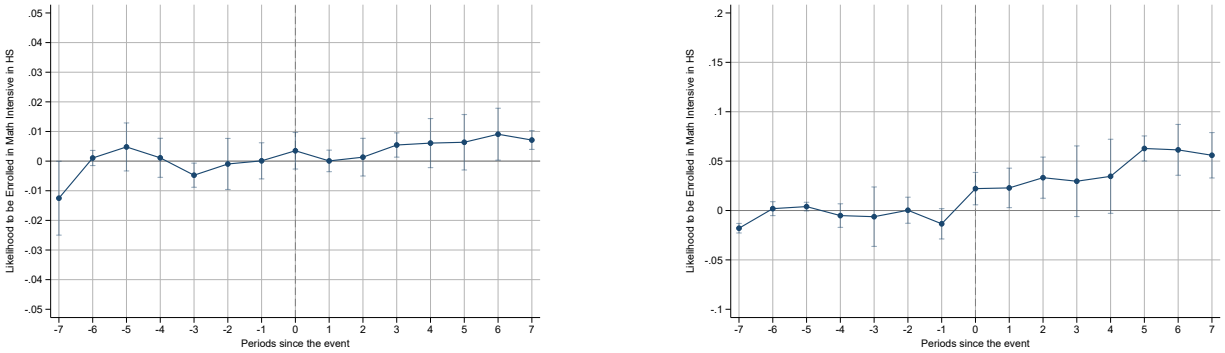
	Women		Men	
	(1)	(2)	(3)	(4)
Tracks				
Academic	-0.000547	-0.00380*	-0.00737***	-0.00526**
	(0.00396)	(0.00224)	(0.00194)	(0.00218)
Vocational	-0.000540	0.00279	-0.0113*	-0.0130*
Baccalaureate Degree	(0.00494)	(0.00345)	(0.00620)	(0.00679)
Vocational	0.0100	0.00846***	0.0277***	0.0241*
Non-Baccalaureate Degree	(0.00859)	(0.00323)	(0.00778)	(0.0123)
N	4856050	4856050	4761437	4761437
Fields				
Computer Science	-0.00000163	0.000000520	0.0000891	0.0000844
	(0.00000788)	(0.00000923)	(0.0000655)	(0.0000593)
Math-intensive	0.00433	0.00448*	0.0449***	0.0416***
	(0.00274)	(0.00258)	(0.0123)	(0.0112)
Unbiased Science	-0.0181***	-0.0153***	-0.0134*	-0.0126*
	(0.00513)	(0.00424)	(0.00753)	(0.00714)
N	1364023	1364023	1764163	1764163
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the Base Centrale Scolarité dataset, which contains information on high school students in France. The table shows results for students enrolled in their first year of high school of the tracks (*Seconde*) as well as students in vocational tracks for the fields of study. The dependent variables are equal to one if the student is enrolled in a certain track or field in high school. Controls include age and socio-economic background. Results are clustered at the county level.

on enrollment in math-intensive tracks of 0.4 pp for women compared to a baseline control group enrollment rate of 5% in these fields, an 8% decrease. This shift appears to be accompanied by a decrease in unbiased scientific fields by 1 pp (a 20% decrease compared to the baseline), possibly reflecting a substitution effect toward math-intensive fields among women. The results in columns 3 and 4 of Table 3 indicate a positive and significant effect on men's participation in math-intensive tracks of 4 pp (approximately 6% increase) as well, alongside a marginally significant decrease in enrollment in unbiased scientific fields. These effects persist through to the final year of high school. [19]

19. In addition, I also perform the same analysis for the academic tracks. Students in the academic tracks can specialize in Humanities, Economics and Social Sciences and Sciences. Table A12 shows a decrease in the likelihood of being enrolled in humanities and an increase in scientific tracks for men. These results are less straightforward to interpret : indeed, many factors influence the choice of field of study in the academic tracks beyond preference for certain disciplines. For instance, the Science specialization is considered more prestigious and can allow students to also enroll in prestigious humanities or social science fields in higher education.

Figure 4 – Event-Plot - Likelihood to Enter a Math-Intensive Field in High School



(a) Women **(b)** Men

Notes : Event-study graph using *csdid* from Callaway and Sant'Anna (2021). I use the Base Centrale Scolarité dataset, which contains information on high school students in France. For this analysis, I focus on students enrolled in their first year of high school. The dependent variable is the likelihood of being enrolled in a vocational math-intensive track in high school. Controls include age and socio-economic background. The dataset starts in 2004 so the first program, Landes, is excluded from the analysis since it is never untreated in the *BCS* data. Results are clustered at the county level.

Figure 4 illustrates enrollment trends in math-intensive specializations for men and women. The effect appears consistent over time and may even strengthen for later cohorts, amplifying the programs' effects on subsequent cohorts. Furthermore, the parallel trend assumptions seem to hold, supporting the validity of these results.

Finally, a key question of this paper is to understand whether universal exposure to gender-biased objects can foster preference for science for women, and potentially help bridge the gap. Is the gender gap in math-intensive fields increasing or decreasing ? I use OLS and report the interaction between treatment and gender in Figure A13 (As Callaway and Sant'Anna (2021) method does not allow for interactions). The analysis reveals a positive interaction effect $Treated \times Women$, although non-significant. This suggests that, while the effect for women is larger compared to the control group than for men, it did not exceed the effect for men in the treated group regarding vocational specialization in math-intensive tracks. As a result, the gender gap was neither reduced nor increased. These results should be interpreted cautiously since I used an OLS method, which is suboptimal for a staggered difference-in-differences setting.

In summary, the programs increased students' likelihood to enter vocational tracks and specialize earlier in scientific fields, particularly in male-dominated fields. The subsequent question is whether this shift affected students' choices in higher education.

6.2 Higher Education

The results from high school suggest three potential hypotheses about the impact of the programs on higher education. First, the movement toward more vocational tracks may have been driven primarily by students who were already less likely to pursue higher education, meaning the programs would have had a minimal impact on higher education outcomes for this group. Second, the programs may have had a longer term effect, were students changed tracks in high school and still entered higher education institutions and choosed scientific fields. Finally, some students may have been affected only after reaching higher education, particularly those from academic tracks where specialization opportunities in high school were limited. For these students, the programs might have encouraged a shift toward science-related fields or more technical studies later in their academic journey.

The next analysis examines the impact of the programs on students' subsequent choices in higher education. Table 4 presents estimates of educational choices using data from the OVE waves, conducted every three years between 1994 and 2016. Focusing on columns 1 and 2 of Table 4, the results show a positive and significant effect of the program on women's participation in math-intensive subjects, mirroring the high school findings. Specifically, after including covariates, the effect size is 2 pp, representing a 33% increase from the baseline. As in high school, the results for unbiased scientific tracks remain negative but statistically insignificant. The second part of Table 4 reports outcomes for more aggregated fields of study, while the third part examines specialized tracks, including Advanced Vocational programs (two-year vocational degrees) and IUT programs (more academically oriented but highly specialized two- to three-year degrees). Women are 3 pp more likely to enroll in these tracks, consistent with the observed shifts in high school tracks, as these programs represent natural continuations for students from vocational or technological tracks in secondary education.

Turning to men's educational choices, shown in columns 3 and 4 of Table 4, the analysis reveals a positive and significant effect for math-intensive tracks of 6 pp, a 28% increase compared to the baseline. For unbiased scientific fields, the effect is modestly significant but sensitive to the inclusion of covariates. Finally, dynamic effects for both women and men are illustrated in Figures A8. The effects are more pronounced in the earlier years for both genders. [20]

Due to differences in survey design between the historical waves and the last three waves, the analysis of the program's effects is limited to more aggregated fields and tracks. However, by focusing

20. The large confidence intervals can be partly attributed to weighting adjustments and the limited number of women in science-related fields per year, as highlighted by Callaway and Sant'Anna (2021), who suggest reporting aggregate results in such contexts.

Table 4 – ATT - Educational Choice in Higher Education

	Women		Men	
	(1)	(2)	(3)	(4)
Subfields				
Math-Intensive	0.00437	0.0216***	0.0652***	0.0687***
	(0.00475)	(0.00367)	(0.0203)	(0.0176)
Unbiased Science	-0.00181	-0.0167	0.0172*	0.00168
	(0.00578)	(0.0106)	(0.00927)	(0.0113)
N	81017	79462	44591	43715
Fields				
Humanities and Social Sciences	-0.0382	-0.0426	0.0129	-0.0254
	(0.0620)	(0.0594)	(0.0344)	(0.0622)
Law and Economics	0.00609	-0.0162	0.0101	-0.0152
	(0.0170)	(0.0276)	(0.0293)	(0.0350)
Science	0.00535	-0.00506	0.0680***	0.0504***
	(0.0133)	(0.0187)	(0.0111)	(0.0183)
Health	-0.0390	-0.0173	-0.00106	-0.000836
	(0.0359)	(0.0407)	(0.0309)	(0.0210)
N	81008	79453	44585	43711
Tracks				
IUT	0.0116*	0.0338**	-0.0149	0.0172
	(0.00666)	(0.0155)	(0.0319)	(0.0397)
Advanced Vocational	0.0297***	0.0358***	-0.0789	-0.0628
	(0.0108)	(0.00596)	(0.0923)	(0.0614)
Elite Preparatory	-0.0507	-0.0419	-0.0493*	-0.0140
	(0.0502)	(0.0397)	(0.0282)	(0.0427)
N	81008	79453	44585	43711
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the OVE data set 2010, 2013, and 2016 and the historic waves restricted to students between 17 and 35 years old, who graduated in metropolitan France and are enrolled in initial training. The dependent variable is the likelihood of entering a certain fields. Controls include age and parents' socio-economic category. Results are clustered at the county level, and weighted using the OVE's administrator weights.

on the most recent waves—2010, 2013, and 2016—it is possible to examine specific tracks and fields in greater detail, and especially engineering schools. Table A15 and Figure A9 presents these results. For women, the program effect extends to engineering schools, with a 3 percentage points increase, and shows a negative effect for humanities. For men, the results indicate a positive effect for computer

science tracks.

I ask the same question as for the high school results : is the gender gap in math-intensive fields increasing or decreasing ? The effect is larger in magnitude for women than men, suggesting the programs benefit women more. Again, I use OLS and report the interaction between treatment and gender in Table A16. The analysis reveals an imprecise but positive interaction effect $Treated \times Women$, strengthening the conclusion that women increased their likelihood to enter math-intensive tracks relatively more than men. Again, these results require caution, as the OLS method used is not ideal for a staggered difference-in-differences approach.

Table A17 displays the combined results for both genders, which show a positive, significant effect on both math-intensive and broadly scientific field enrollment, supporting the findings of the stratified results.

6.3 Labor Market

Finally, one might wonder if the positive education effect enabled more individuals to enter male-dominated occupations or industries. To do so, I use the *Enquête Emploi (EE)*, including anyone aged 15 and over living in mainland France. The main results are shown in Table A18 and in Figures A10 and A11. Table A18 shows a positive effect on women's occupation in math-intensive and computer science-related occupations. The effect is negative for men. Estimations from both figures show imprecise results. We can also note that there is no obvious pre-trend, strengthening the fact that the effect on education is not due to a pre-existing active labor market in these industries that would have incentivized students to invest in their education expecting better labor market returns in these occupations or industry.

There are multiple reasons why the labor market effects may not strongly follow the educational results : First, tracking individuals who benefited from the programs in their careers is challenging : indeed, the data does not account for worker mobility across counties ; if treated individuals moved for study or work, I cannot identify their country of origin. In Table A19, I assess the likelihood of studying in another county or another *académie* for treated students : the results are indeed overall positive, especially for men, consistent with the rather insignificant effect in terms of labor market. [21] Next, despite careful definitions, some treated individuals may be working in jobs not identifiable as *Computer Science*, *Math-Intensive* or *Unbiased Science* using the EE, leading to measurement

21. *Académies* are geographic administrative units of the Ministry of National Education and the Ministry of Higher Education and Research.

errors. [22]

6.4 Heterogeneity Analysis by SES

In Section 3, I showed that SES influences access to and use of computers, suggesting that program responses might differ by SES and potentially explain some of the earlier findings. Notably, the sensitivity of certain effects, especially for women, to the inclusion of covariates suggest potential SES-driven differences. This section examines these heterogeneous effects in detail. Notably, SES-driven heterogeneity could manifest in two opposing ways : High-SES students, having greater access to resources and technology prior to the programs, might exhibit weaker reactions to the additional resources. Conversely, they may benefit more from parental investment in digital skills, which may be crucial for leveraging the provided resources effectively. High-SES students also face fewer financial barriers, making them more likely to enroll in certain tracks and fields.

Table A20 presents the high school results stratified by SES. Among women, the tracking effects—characterized by a decrease in enrollment in academic tracks and an increase in vocational tracks—are primarily driven by higher-SES women. Conversely, the increase in participation in math-intensive tracks is predominantly observed among lower-SES women. These seemingly opposing trends may be explained by pre-existing differences in track selection probabilities (See Figure A13). High-SES students are generally less likely to choose vocational tracks. Consequently, the program may have encouraged higher-SES women to specialize earlier, leading to increased enrollment in vocational tracks at the higher education level. Meanwhile, for lower-SES women, who are already more inclined toward vocational tracks, the program appears to have opened pathways into math-intensive fields.

This SES-based pattern persists in higher education, as shown in Table A21. While the results lose statistical significance, the positive effects on women's participation in math-intensive tracks remain driven by lower-SES individuals.

For men, the analysis reveals no significant SES-based heterogeneity. Both low- and high-SES men contribute equally to the observed effects, suggesting a more uniform response to the programs across socio-economic backgrounds.

These findings align with evidence from Section 3 and Figure A7, which showed that lower-SES individuals use computers more intensively. A possible explanation is that lower-SES students may

22. I define two variables for math-intensive tracks : *Math-Intensive* and *Math-Intensive Alternative* with a broader definition. Figure A12 and Table A18 show positive, significant results for *Math-Intensive Alternative* for men, contrary to the other definition of math-intensive tracks, suggesting that indeed, the results might be driven by the challenges in identifying relevant occupations and industries.

have had more time on the computer, potentially fostering preferences that diverge from traditional social norms and encouraging entry into these fields. In contrast, higher-SES students may have benefited from structured and environments where gender norms are more enforced, for instance parents. While this hypothesis cannot be empirically verified here, I explore related literature on major selection to provide further context in the mechanism sections.

7 Robustness checks

I conduct a set of robustness checks to ensure the validity of the results.

Identification Strategy - One can argue that there might be other factors or public policies that influence students' likelihood of being enrolled in different scientific fields.

Another related policy that may have impacted student interest in science is the *B2i* program, which aimed at expanding students' digital skills by including a mandatory test of computer skills at the end of middle school. The *B2i* was implemented around the same time as the programs. While it is possible that this policy increased students' interest in computer science, it was a national-level reform, and no records show that the treated counties implemented it more intensively.

However, county authorities might have implemented other policies unrelated to ICT that could have impacted students' choices. Notably, all treated counties leaned left politically, either historically or due to recent elections (the 1998-2008 period saw a significant political shift, with numerous counties moving leftward and few moving rightward). Left-leaning counties might be more likely to support free computer programs and also more likely to implement other policies shaping students' decisions, especially in sciences. As a robustness check, I leverage the variations in county elections, particularly focusing on switchers—counties that transitioned to the left. In Table A22 for high school tracks, and in Table A23 for higher education, I narrow down the control group to include originally left-leaning counties only (columns 1 and 2), counties that switched in 2001 (columns 3 and 4), 2004 (columns 5 and 6), and 2008 (columns 7 and 8). The results continue to hold for men, further reinforcing the conclusion that the programs themselves primarily influenced the observed outcomes. For women, the effect remains the same as in Tables 3 and 4, but are slightly less precise for high school results, potentially due to less observations. Overall, this validates that the effects are due to the programs and not auxiliary policies.

The main results indicate that women are more likely to enter specific institutions, such as engineering schools or advanced vocational tracks. This raises the possibility that changes in the supply

of higher education institutions could be driving the results. If the supply increased concurrently with the programs, possibly due to political efforts to enhance the county's technological environment, the observed effects might be partly attributed to students having more opportunities to study closer to home, or to these institutions influencing the technological environment of the counties more broadly. To alleviate this concern, I use administrative data from the Ministry of Education which includes information on all public higher education institutions to calculate a centrality measure. [23] To calculate proximity to such institutions, I use the mean longitude and latitude of all cities in each county and their distance to each institution offering computer science training and I define the measure of closeness centrality as :

$$C(s) = \frac{1}{\sum_i d(c,i)} \tag{2}$$

c being the counties, i the institutions, and $d(s,i)$ the distance of each county to each institution. I add this measure as a control variable in the analysis in Tables A24 and A26. The results are similar to the main results. Alternatively, it is possible that what matters is the increased access to certain types of institutions, and especially ones that would strengthen the presence of technology in these counties. To rule out this hypothesis, I use hand-collected data from higher education institutions delivering computer science diplomas as a proxy for tech-oriented institutions to calculate the same centrality measure, and I obtain the same results in Tables A25 and part two of A26. [24]

Finally, I check that the effect is not driven by better access to the internet. Indeed, broadband access expanded in the early 2000s, approximately at the same time as the free computer programs. Hence, one possibility is that the observed effects are not stemming from the programs but from the extended access to the resources of the internet. To rule out this concern, I use data on broadband access in France from the work of Malgouyres et al. (2021). More specifically, I use the first year of broadband access at the city level as defined by Malgouyres et al. (2021), and calculate the average per county (using both the non-weighted - type 1 - and the weighted results by the city area - type 2. See Malgouyres et al. (2021) for more details). In Tables A27 for Type 1 and A28 for Type 2 for results in high school and A29 for the higher education results, I use these measures as controls : this does not affect the results.

23. Data collected from open source in 2023.

24. I did not add business schools (their main focus being business and not computer science, even though a few of them started offering computer science diplomas (mainly master's degrees), as well as training centers (that are more targeted to continuous training).

Estimation choices - In the section 6, the main analysis uses all counties in metropolitan France as the control group. One might worry that this broad choice of control might not be relevant to reflect a change in some specific counties. I use an alternative control group restricted to counties in the same *région* as the treated counties : counties in *régions* Bretagne, Picardie, Provence-Alpes-Côte d'Azur, Aquitaine and Limousin.[25] Results using this restricted control group are in Tables A30 and A31, and show similar results as the main specification, again with the effect for women in math-intensive tracks being sensitive in terms of standard error due to the reduced sample, although the effect is actually larger in magnitude when only restricting to control counties in the same *région* (0.7 pp increase).

Next I reproduce the results with the Two-Way Fixed-Effect model. As mentioned, this paper goes beyond the traditional specification by incorporating recent advancements in the Difference-in-Differences (DiD) methodology for staggered treatment settings. Recent studies have highlighted that the conventional DiD assumption of stable treatment effects over time does not hold in staggered treatment designs (Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021). This issue is particularly relevant in this context, as the rapid expansion of ICT in France during the 2000s suggests that students exposed to the programs earlier (in Landes, Bouches-du-Rhône, and Ille-et-Vilaine) may have experienced different impacts compared to those exposed later. Indeed, Tables A32 and A33 shows less precise and insignificant, strengthening the validity of the methods by Callaway and Sant'Anna (2021). To make sure that the difference in the two estimation methods are driven by the time-varying heterogeneity, I show the effect for the two "generations" of programs separately : Tables A34 and A35 shows that the effects are stronger for both men and women when I exclude the last two programs, Oise and Corrèze.

Finally, as mentioned in Section 4, the possibility of endogenous sampling introduces a potential bias that could inflate results. Students who benefited from the programs might be more likely to have better computer access in the future, increasing survey participation likelihood, particularly for those in scientific tracks. To mitigate possible sample bias, I incorporate the weights provided by data administrators in the main results. I plot the non-weighted results in Table A36. The unweighted estimates differ somewhat from the main results. Notably, the magnitude and the precision of the effect for math-intensive fields increases for both women and men. This highlights that the endogenous sampling partially plays a role : the programs seem to have increased the likelihood

25. Note that the administrative classification was modified in 2018, to create only 13 *régions* instead of 22. I use pre-reform classification, as the programs were implemented before 2018.

to answer the survey, potentially through better access to technology to answer the survey online. However, correcting for endogenous sampling using weights as recommended by Solon et al. (2015) does not eliminate the effect, suggesting that endogenous sampling cannot be the sole explanation.

Placebo Analysis - To further test the validity of the main results, I perform two placebo estimations. First, I reproduce the main analysis but use a different set of counties as the treated units. I find no significant results in Table A37 and A38, as coefficients are mostly insignificant. Next, I use placebo using two placebo years of treatment : 3 years prior to the actual treatment and 4 years before in Tables A39 and A40 (I can only perform this test for the higher education results as the BCS data does not have enough historical depth to make sense of these results). Overall, the placebo tests suggest the main results are driven by the programs being studied, and confirm the validity of the conclusions.

8 Mechanism

So far, I have shown that the programs increased the likelihood of both women and men entering scientific fields, especially math-intensive and male-dominated fields, with a stronger effect for women. The next section I use the literature to discuss the different mechanism that could explain the results.

To address remaining explanations, I leverage the simple choice model developed by Zafar (2012) to discuss other alternatives. In Zafar (2012) model, a student's choice of major is driven by the utility or satisfaction they expect to derive from that educational path. [26] While there are various factors influencing their utility function, Zafar (2012) finds that only a few significantly determine the choice of major itself : the perceived likelihood of graduating from the chosen track, the expected enjoyment or preferences for the coursework, and parental approval or expectations.

Academic Performance - First, one possibility is that the programs improved actual or perceived academic performance, influencing long-term choices in higher education. In Table A41, I test this hypothesis by assessing the probability of students sitting and passing the Baccalaureate exam. The results are mostly insignificant. The fact that such programs would not necessarily affect student's academic achievement mainly aligns with previous findings on the effects of computers and technology on children's academic outcomes (Fairlie, 2005; Fairlie et al., 2010; Angrist and Lavy, 2002; Rouse and Krueger, 2004; Fairlie and Robinson, 2013; Malamud and Pop-Eleches, 2011). However,

26. There is a larger theoretical and empirical literature on college major choices summarized in Altonji et al. (2016).

I cannot completely rule out the possibility that academic achievement was affected by the programs in other margins. The fact that students are more likely to enter less academically challenging tracks, for instance, could be a signal of change in perceived or actual performance. However, while it's possible that the effect is partially explained by academic performance, the fact that students choose math-intensive fields – and especially women, who are very much under-represented in these fields – is hard to explain through a performance effect alone, as there are also female-dominated tracks that are less academically challenging.

Skill Acquisition and Enjoyment - On the other hand, the programs might have affected two other important factors of educational choices : the expectation of graduation through skill acquisition, and the preferences for the courses. Indeed, previous literature on free computer programs in other contexts has found increases in technology use and skills (Angrist and Lavy, 2002; Rouse and Krueger, 2004; Malamud and Pop-Eleches, 2011; Fairlie and London, 2012), but also in the French context : Fougère et al. (2021) show that exposure to computers in middle school through a targeted program implemented in 2015 increased students digital skills, and especially for under-privileged students. Following the qualitative work of Perronnet (2023) discussed earlier, this hands-on experience with technology could have sparked new interests and increased enjoyment of math and tech-related coursework. Therefore, access to computers may have allowed students, particularly low-SES students who previously lacked exposure, to build technical skills and gain hands-on experience. This increased exposure likely fostered confidence in their ability to succeed in technology-related fields. This also aligns with research on STEM-related toys, which has shown that access and engagement with such toys can significantly shape beliefs, preferences, and attitudes towards STEM fields (Francis, 2010; Sherman and Zurbriggen, 2014; King et al., 2020).

Parental Expectations - The programs might have changed parental expectations, especially by signaling the value of tech-related tracks. The government's provision of free computers to students may have signaled the importance and value of technology-related fields in the future labor market, as partially intended by the policymakers (Khaneboubi, 2013). This external signal could have influenced parental expectations and, as a result, these parents may have encouraged their children to pursue lucrative technology tracks and steered their children towards math-intensive programs or engineering schools.

Gender Norms - One last important factor has to be accounted for : the gender difference in choices of tracks. Indeed, the fact that the programs induced an increase in female participation in male-dominated tracks calls for attention. This attention to gender in the choice of major refers to a

closely related paper to Zafar (2012) : Zafar (2013). In this paper, the author accounts for the gender heterogeneity and finds that enjoying coursework and gaining parents' approval are important determinants in the choice of major for both genders, but males and females differ in their preferences. In the gender literature, preferences usually reflect stereotypes that are either internalized or pushed on individuals by social pressure (Bertrand, 2020). Therefore, the role of stereotypes and social norms here can help us understand this gendered effect. First, the free computer programs may have countered the internalization of gender-stereotypical norms that perceive technology as an inappropriate or unsuitable field for girls by providing universal and substantial exposure to technology (Bertrand, 2020). Second, this exposure likely shifted external social norms as well, making computer usage more socially acceptable for girls and reducing the stigma or disapproval associated with deviating from gender norms (Bertrand et al., 2015; Folke and Rickne, 2020; Bursztyn et al., 2017, 2018), considering the role of parents' expectations in choices of major, but also the role of teachers' biases (Carlana, 2019; Mengel et al., 2019). Finally, by changing norms, the programs may have addressed the lack of information available to girls in math-intensive and tech sectors, which can perpetuate gender biases and prevent the pursuit of such careers (Hastings et al., 2015; Wiswall and Zafar, 2015; Ding et al., 2021; Breda et al., 2023; Kessel et al., 2021), and even more broadly access to role models and change in time use, as evidenced by La Ferrara (2016) about per edutainment resources. Hence, increased access to information about potential tracks and wages, could have encouraged more girls to consider viable options in math-intensive and tech-related areas.

9 Conclusion

This paper investigates the long-term impact of free-computer programs on educational choices, particularly for women in math-intensive fields. I leverage large-scale free computer programs implemented at the county level in France that provide every middle school student with a personal computer. I first document a gender gap in computer usage and confidence among middle school students, despite similar access rates. I also show that unbiased exposure and use to gender-biased objects could play an important role in shaping later educational choices. Using a difference-in-differences strategy, I use the large-sale free computer programs to causally show that reducing the unbalance in access to technology significantly increased the probability of women entering math-intensive tracks. For men, the programs increased the likelihood of entering math-intensive tracks as well, but not enough to increase the gender gap, still participating to promoting women in male-dominated fields. Exploring the mechanisms, I discuss how exposure to free computer programs

increased enrollment in math-intensive educational tracks for both genders through multiple mechanisms : parental expectations, increased skills in technology-related tracks, and enjoyment. To explain the decrease in the gender gap in these fields, I discuss the possibility that the programs helped counter internalized gender norms that viewed male-dominated STEM fields as unsuitable for girls. Early technology exposure may have shifted societal perceptions to increase the external social acceptance of girls using computers and building related technical skills as well.

An important question arises : how applicable are these findings today when most children have access to computers ? There are two key points to consider. First, access to technology remains unequal globally. In 2023, around 2.6 billion people – one-third of the world's population – still lacked internet access (The World Bank, 2024). While over 90% were online in high-income nations, only 25% of the population in low-income countries could access the internet. Promoting equitable technology access and nurturing young girls' aspirations for high-opportunity careers remains crucial in many parts of the world. Secondly, in affluent countries like France, this research speaks to more than just computer exposure. It highlights the impact of universal access to formative tools and experiences that shape vocations, build skills, and enable individuals to transcend restrictive gender norms. The findings connect to studies on gender-biased objects (Francis, 2010; Sherman and Zurbriggen, 2014; King et al., 2020; Coyle and Liben, 2016, 2020) and public discourse (Russell, 2021) demonstrating how exposure to different objects can indeed influence aspirations and abilities. Thus, while addressing remaining technology gaps, this work underscores the broader need in both resource-poor and affluent contexts : ensuring all children, especially girls, encounter a range of experiences that expand their horizons beyond entrenched social biases.

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Appendices

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A Figures

A.1 Institutional Background

Figure A1 – Timeline of the programs

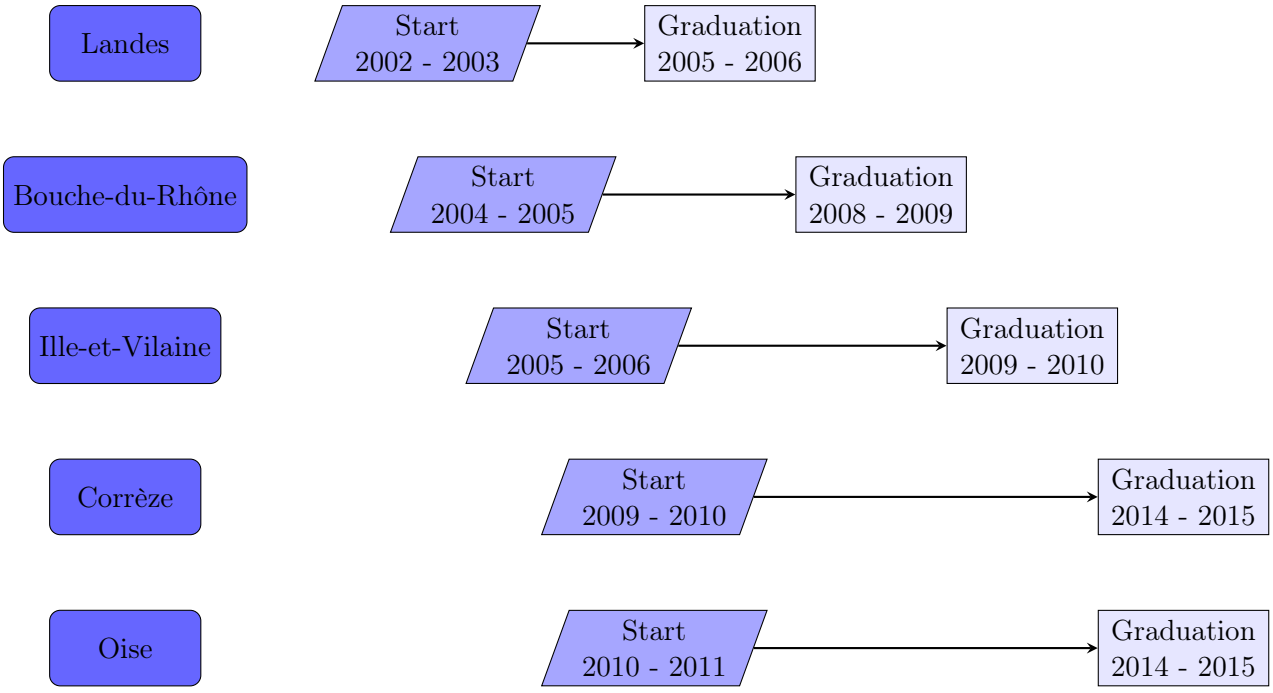
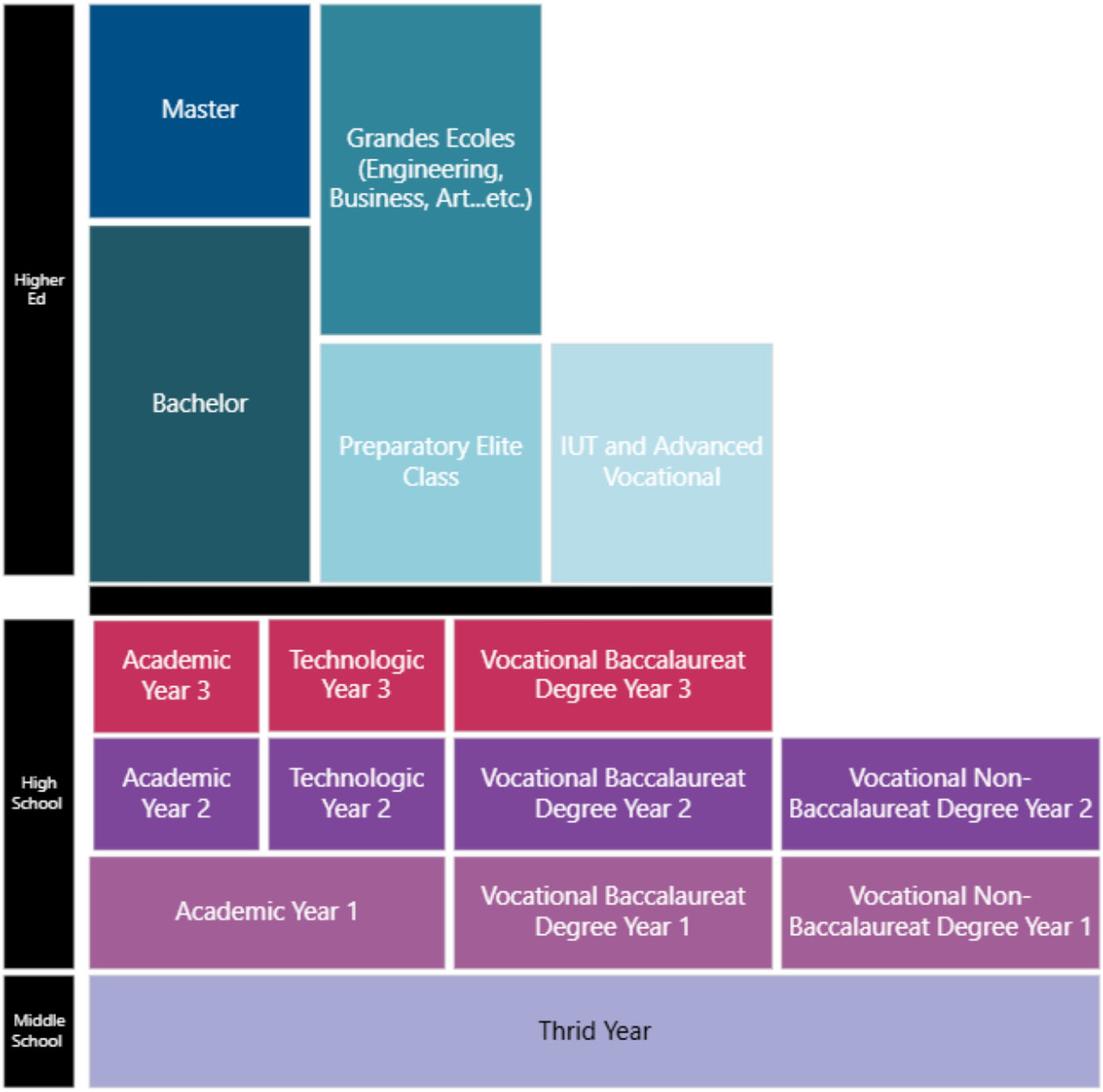
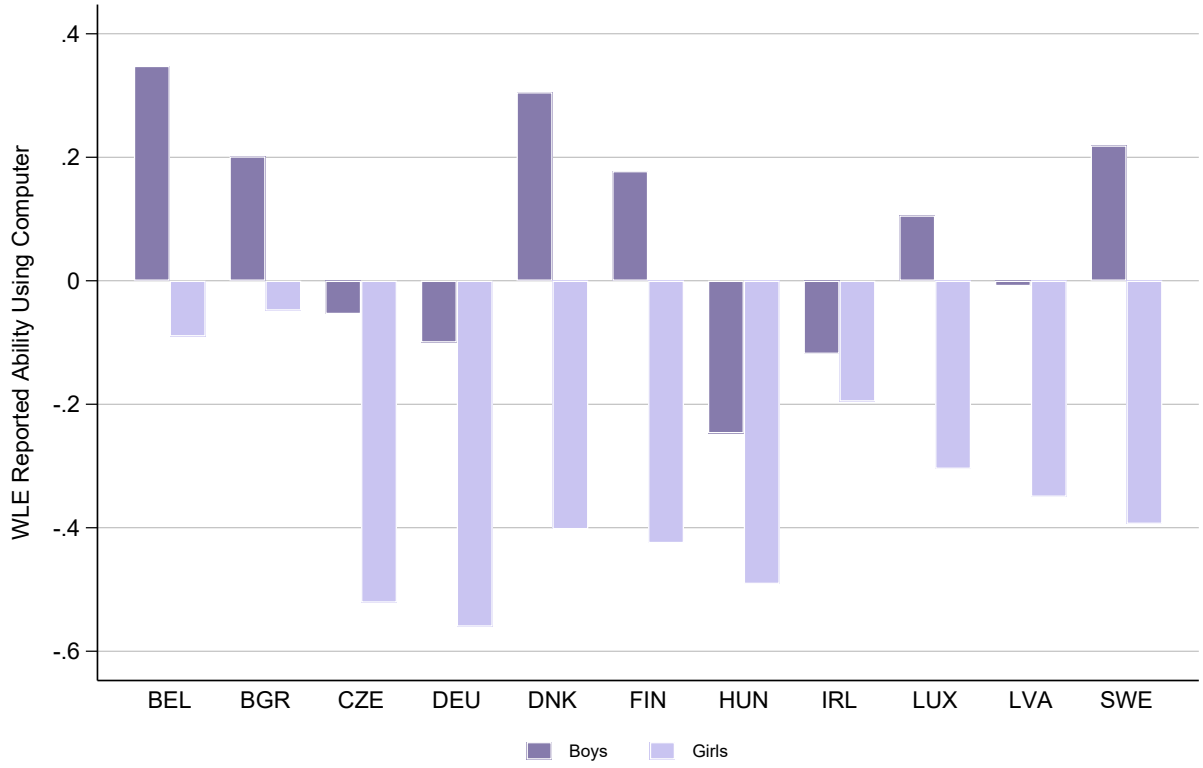


Figure A2 – French Education System



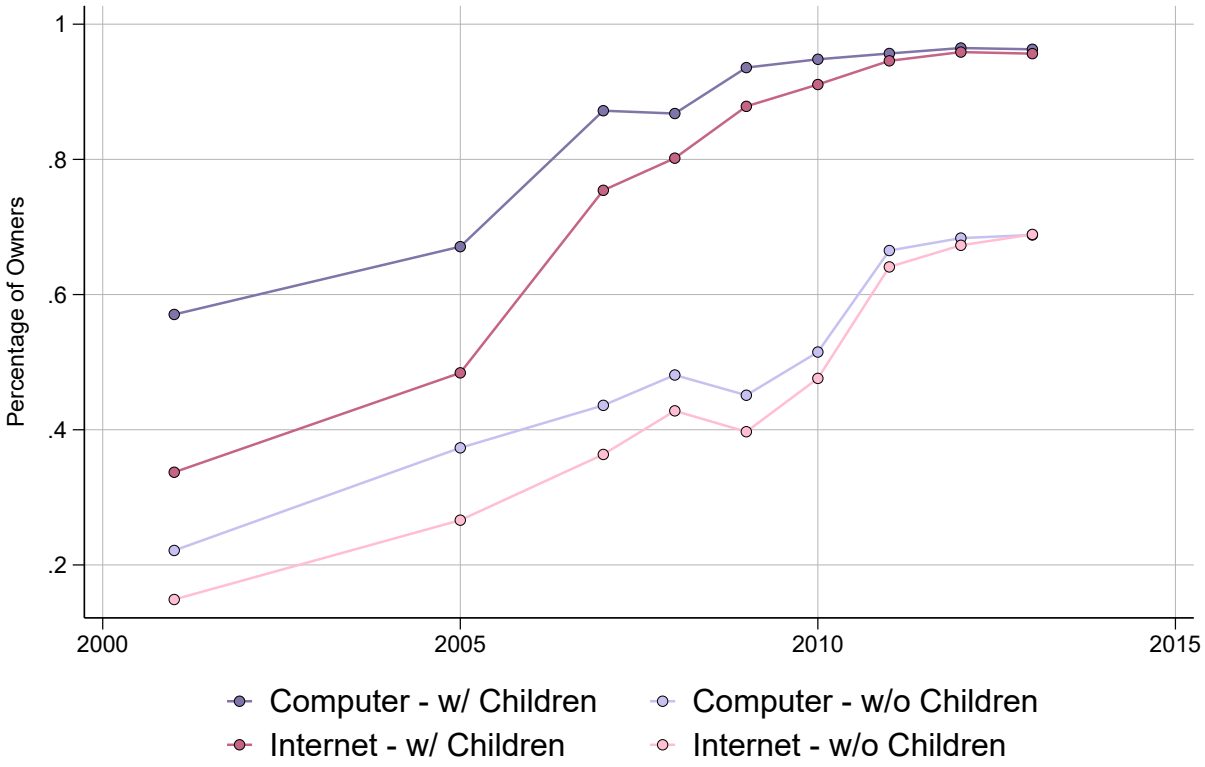
A.2 Exclusion of Girls from Technology

Figure A3 – WLE for the Feeling Comfortable using a Computers - PISA



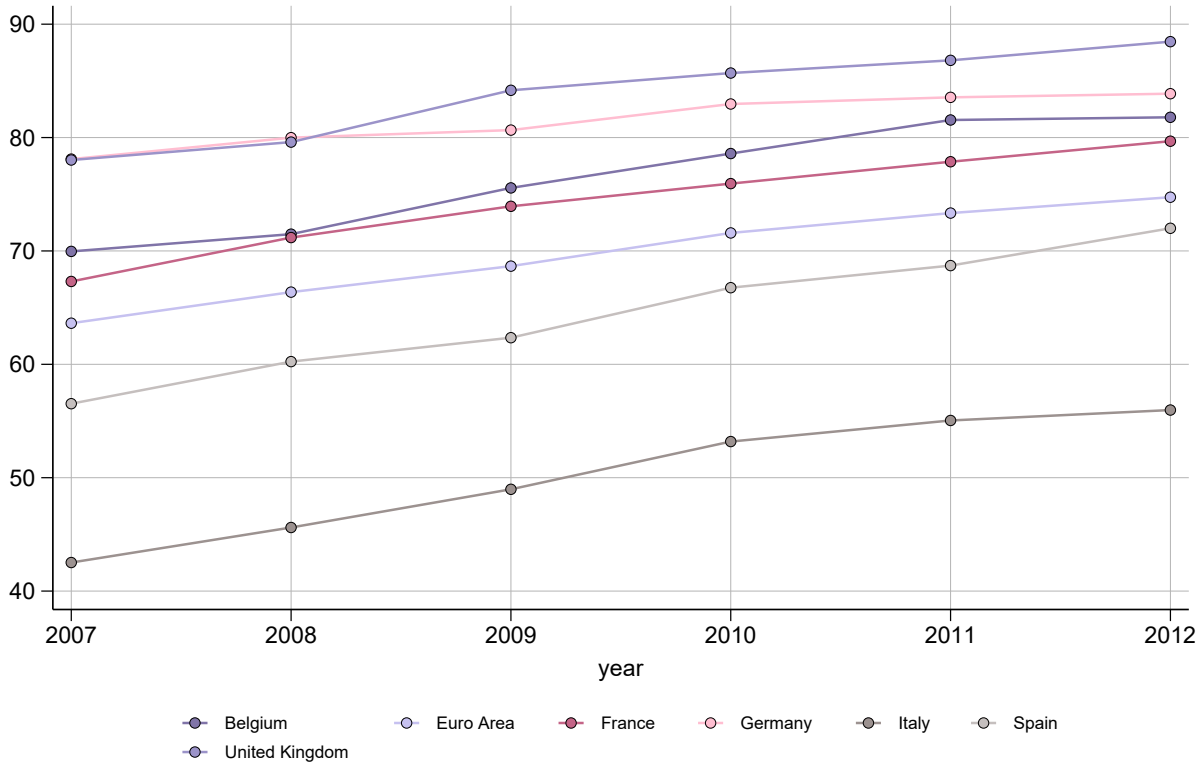
Notes : Data from the PISA 2000 survey. Data are downloaded in STATA format from : Jakubowski and Pokropek (2013). Children are 14 to 16 years old, and I use the question "*How comfortable are you using a computer*". Students can answer *Very comfortable, Comfortable, Somewhat, Somewhat, Not at all comfortable.* Results are then modified using the weighted likelihood estimates procedure as individual scores and transformed to obtain a mean of 0 and a standard deviation of 1.

Figure A4 – Evolution of Computer Ownership and Internet Access - ETIC



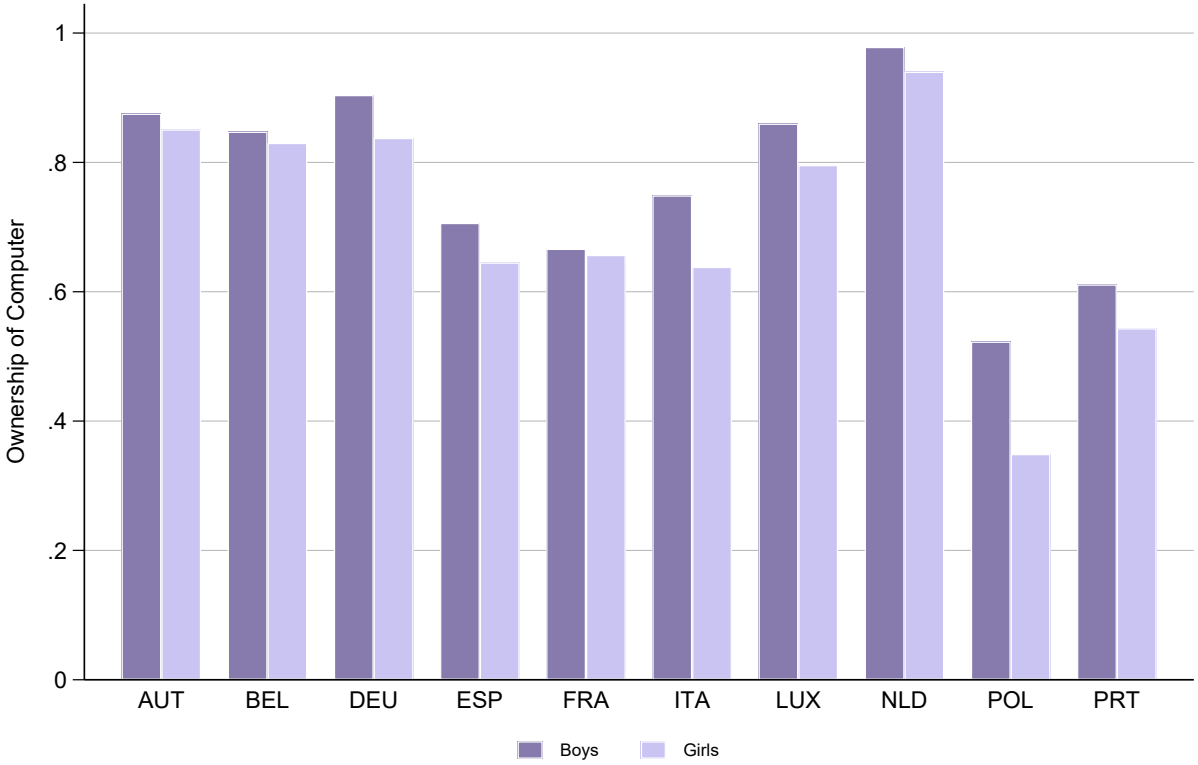
Notes : Weighted average of the share of households owning a computer and having internet access in France between 2000 and 2013 using the *Enquête sur les technologies de l'information et de la communication (ETIC)*. *W/Children* includes only households living with at least one child, *W/O Children* includes only households without children.

Figure A5 – Evolution of Computer Use in the Last Three Months - Eurostat



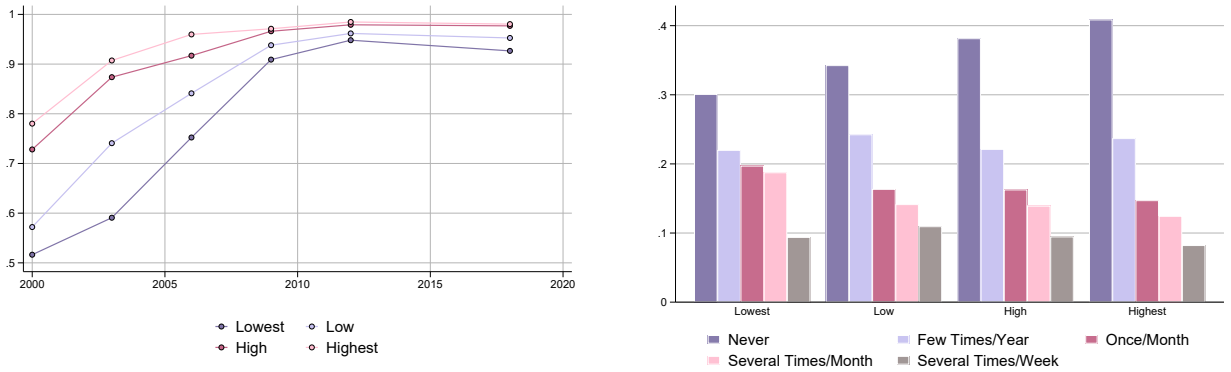
Notes : I use the EU survey on the use of Information at Communication Technologies (ICT) from 2007 to 2012 in households and by individuals available here : Source. I use a dummy variable equal to 1 if the individual report having used a computer in the last three months.

Figure A6 – Ownership of Computer - PISA



Notes : Data from the PISA 2000 survey. Data are downloaded in STATA format from : Jakubowski and Pokropek (2013). Children are 14 to 16 years old, and I use the question of the self-reported availability of a computer at home, 0 being not owning a computer, and 1 being ownership

Figure A7 – Ownership and Frequency of a Computer Per SES



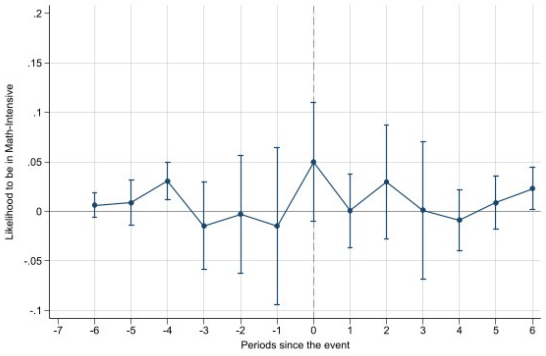
(a) Ownership of computer - PISA

(b) Frequency of Computer Use

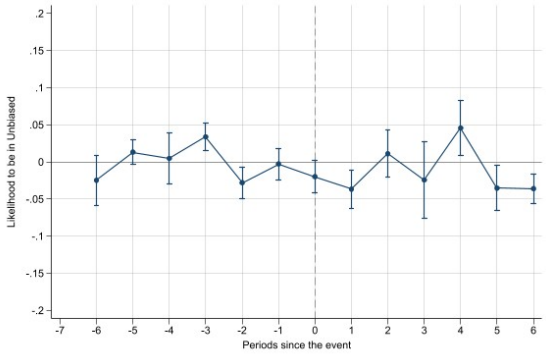
Notes : Data from the PISA 2000 survey. Data are downloaded in STATA format from : Jakubowski and Pokropek (2013). Sub-graph 3a is the self-reported availability of a computer at home : 0 being not owning a computer, and 1 being ownership. Sub-graph 3b uses the question *"How frequently do you use a computer"*, where students can answer Never, Few Times per Year, Once a Month, Several Times/Months, and Several/Week.

A.3 Results

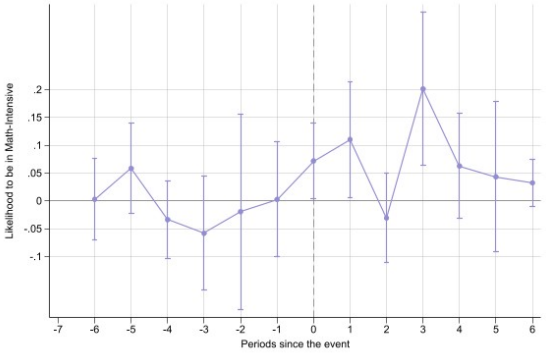
Figure A8 – Event-Plot - Educational Choices in Higher Education



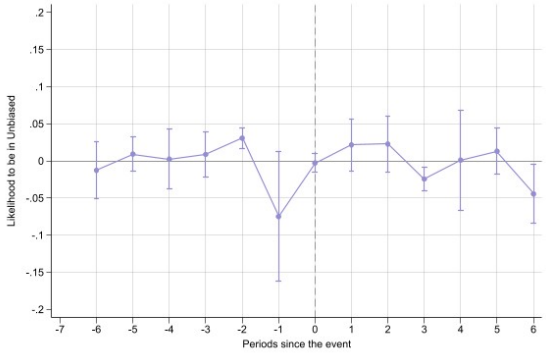
(a) Math-intensive - Women



(b) Unbiased Science - Women



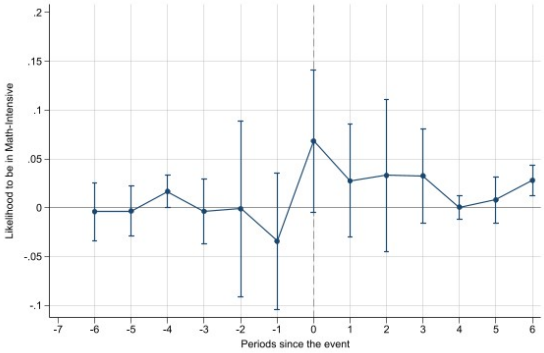
(c) Math-intensive - Men



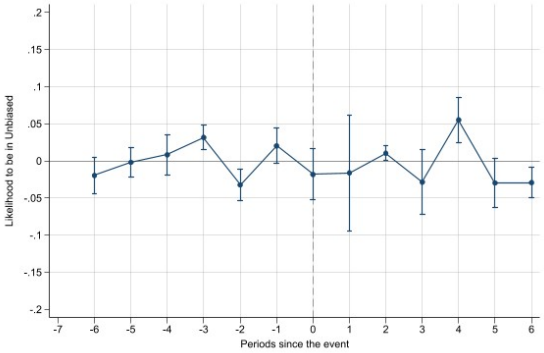
(d) Unbiased Science - Men

Notes : Event-study graph using *csdid* from Callaway and Sant'Anna (2021). I use the OVE data set 2010, 2013, and 2016 and the historic waves restricted to students between 17 and 35 years old, who graduated in metropolitan France and are enrolled in initial training. The dependent variable is the likelihood of entering a certain field. Controls include age and parents' socio-economic category. Results are clustered at the county level, and weighted using the OVE's administrator weights. I restrict graphs to period -7 and period 6 due to a lack of observations before and after.

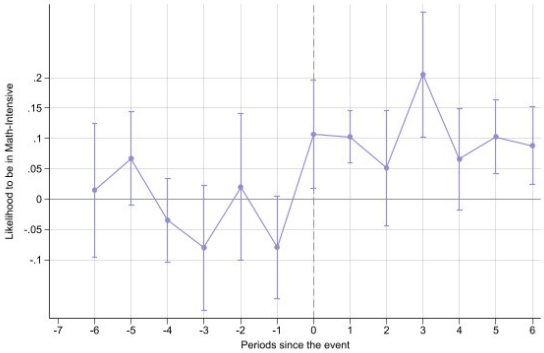
Figure A9 – Event-Plot - Educational Choices in Higher Education - Last Three Waves



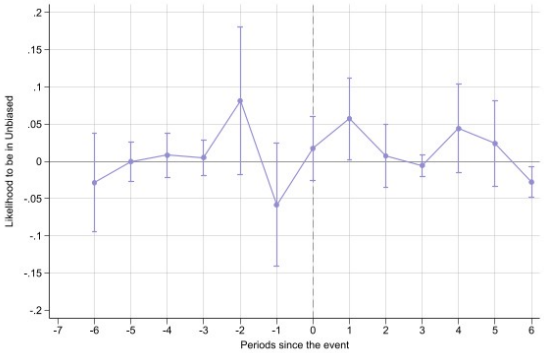
(a) Math-intensive - Women



(b) Unbiased Science - Women



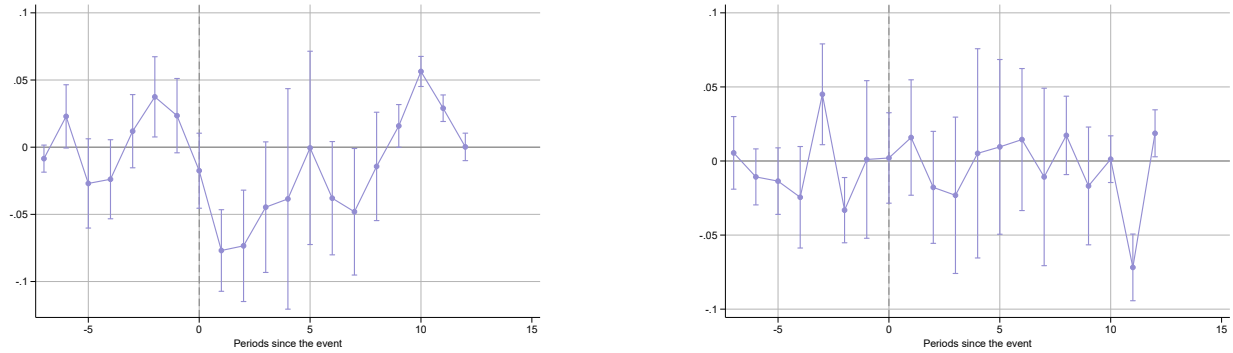
(c) Math-intensive - Men



(d) Unbiased Science - Men

Notes : Event-study graph using *csdid* from Callaway and Sant'Anna (2021). I use the OVE data set 2010, 2013, and 2016 waves restricted to students between 17 and 35 years old, who graduated in metropolitan France and are enrolled in initial training. The dependent variable is the likelihood of entering a certain field. Controls include age and parents' socio-economic category. Results are clustered at the county level, and weighted using the OVE's administrator weights. I restrict graphs to period -7 and period 6 due to a lack of observations before and after.

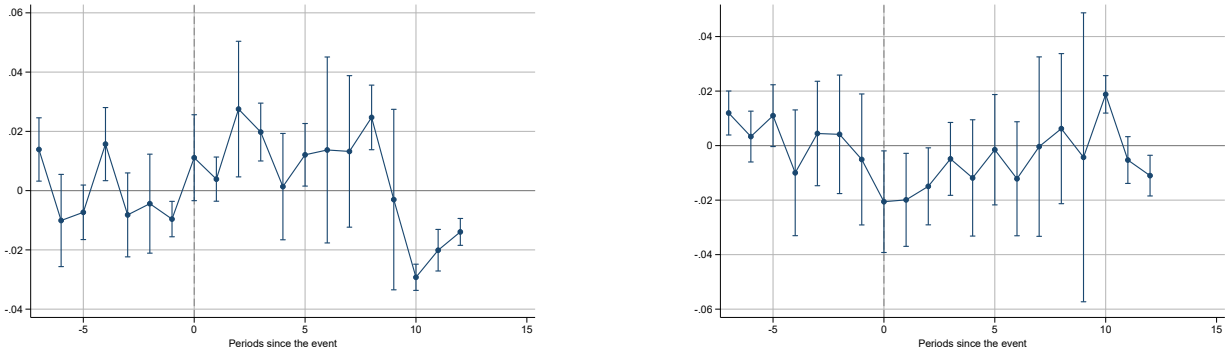
Figure A10 – Event-Plot - Share of Workers in Math-Intensive Profession and Industry at the County Level - Men



(a) Profession **(b)** Industry

Notes : Event-study graph using *csdid* from Callaway and Sant'Anna (2021). The data comes from the EE survey, and I restrict the sample to men aged 15 and older who are currently employed. I construct a panel dataset at the county level covering the years 1984 to 2015. The dependent variables of interest are the likelihood of working in an industry related to mathematics or computer science or having an occupation related to these fields. I restrict graphs to period -7 and period 12.

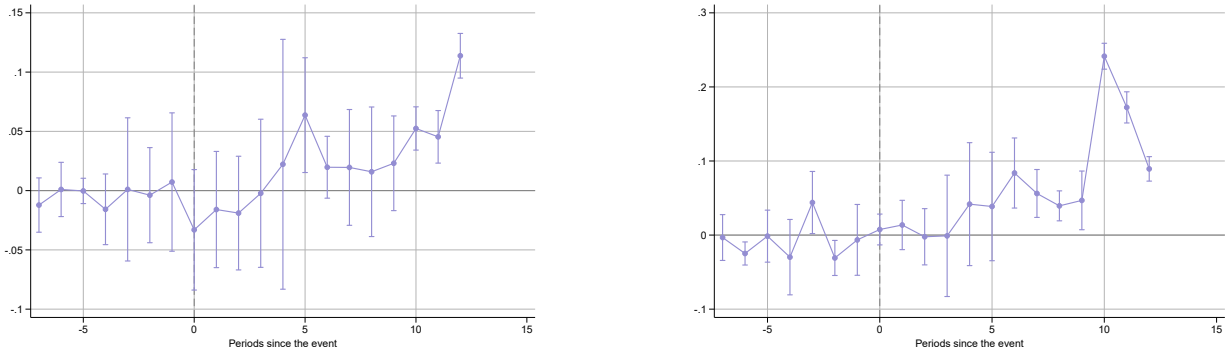
Figure A11 – Event-Plot - Share of Workers in Math-Intensive Profession and Industry at the County Level - Women



(a) Profession **(b)** Industry

Notes : Event-study graph using *csdid* from Callaway and Sant'Anna (2021). I use the EE survey, and I restrict the sample to women aged 15 and older who are currently employed. I construct a panel dataset at the county level covering the years 1984 to 2015. The dependent variables of interest are the likelihood of working in an industry related to mathematics or computer science or having an occupation related to these fields. I restrict graphs to period -7 and period 12.

Figure A12 – Event-Plot - Share of Workers in Alternative Math-Intensive Profession and Industry at the County Level - Men - EE



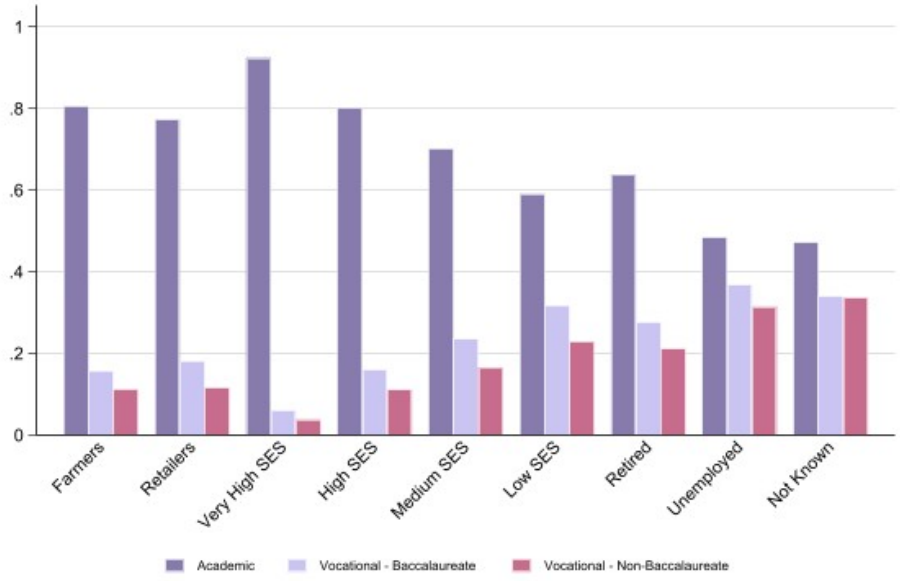
(a) Profession - Alternative

(b) Industry - Alternative

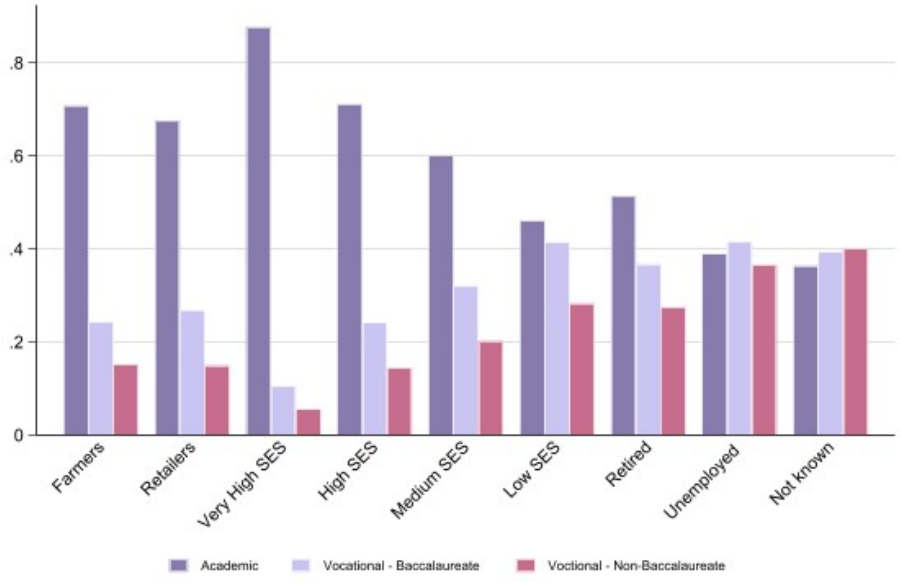
Notes : Event-study graph using *csdid* from Callaway and Sant'Anna (2021). I use the EE survey and I restrict the sample to men aged 15 and above who are currently employed. I construct a panel dataset at the county level covering the years 1984 to 2015. The dependent variables of interest are the likelihood of working in an industry related to math-intensive fields or having an occupation related to these fields. The black line in the event study graphs represents the start of the programs being evaluated. *Alternative* means an alternative and broader definition of Math-Intensive occupations and industries. Refer to the supplementary appendix for more details on the definitions.

A.4 Mechanisms

Figure A13 – Tracks by SES Background in High School



(a) Women



(b) Men

Notes : Descriptive statistics for educational choices variables using the BCS dataset, which contains information on high school students in France. Socio-Economic Background (SES) is defined by the INSEE as in section 4 and referees to the primary carers, usually the father.

B Tables

B.1 Institutional Background

Table A1 – Timeline of the Treatment

	2001-2002	2002-2003	2003-2004	2004-2005	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015
Landes	**Test**	1	2	3	**HS Graduation**	5	6	7	8	9	10	11	12	13
Bouches du Rhone			**Test**	1	2	3	4	**HS Graduation**	6	7	8	9	10	11
Ille-et-Vilaine				**Test**	1	2	3	4	**HS Graduation**	6	7	8	9	10
Oise									**Test**	1	2	3	4	**HS Graduation**
Correze								**Test**	1	2	3	4	5	**HS Graduation**

Notes : Timeline of treatment including test year. *HS Graduation* is the year the cohort is supposed to graduate high school if they do not repeat or skip a year. *Test* is the first year of the program, where only a limited number of class or schools got the computer. This year is not accounted in the estimation.

B.2 Exclusion of Girls from Technology

Table A2 – Ownership of Computer and Engagement With Science

	Study		**Career**		**Advanced Science**		**Project**	
	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys
Owning a Computer	0.0849**	0.0647*	0.0579	0.0397	0.00476	0.0512*	0.0499	0.0581*
	(0.0341)	(0.0356)	(0.0360)	(0.0368)	(0.0248)	(0.0305)	(0.0308)	(0.0347)
N	1982	1825	1984	1826	1982	1822	1983	1826
R^2	0.030	0.080	0.023	0.061	0.022	0.039	0.020	0.046

Notes : Standard errors in parenthesis. This table reports the results of the OLS regression. The table uses the 2006 PISA data focusing on the french sample. The dependent variables are equal to 1 if the students answer strongly agree or agree to the questions : "*I would like to work in a career involving broad science*", "*I would like to study <broad science> after secondary school*", "*I would like to spend my life doing advanced broad science*" and finally : "*I would like to work on broad science projects as an adult*". I control for the parents occupation and education, if they have a desk, a room of their own, a place to study and a dictionary at home.

B.3 Data

Table A3 – Description of the Additional Datasets

Name	Institution	Type of Data	Level	Year
		Individual Level		
Enquete Emploi	Ministry of Labor	Survey of Individual in the Labor Market	Individual	1984 - 2016
Recensement de la population	INSEE	Population census data	Individual	1984 - 2019
PISA	OECD	Representative sample of students in the OECD surveyed on schooling achievement		2000
Enquête permanente sur les conditions de vie des ménages	INSEE	Use and access to ICT		2001
		County Level		
Succès au Baccalauréat	DEPP	Success in the Baccalaureate (High School Grad)	County	2000 - 2016
Taux de Chômage	INSEE	Unemployment rate	County	2000 - 2016
Access Internet Haut Débit	Malgouyres et al. (2021)	Broadband Internet	City Level	1999 - 2007
Principaux Etablissements d'Enseignement Supérieur	MESR	All Higher Education Intuitions	County	2023
Principaux établissementsd'enseignement supérieur délivrant un diplôme en informatique	Hand-Collected	All Higher Education Intuitions Providing a Computer Science Degree	County	2023

Notes : Definition of the different institution : *DEPP* - (*Direction de l'évaluation, de la prospective et de la performance* - *Statistical institute of the ministry of education*) ; *INSEE* - *Institut national de la statistique et des études économiques* ; and *MESR* - *Ministere de l'enseignement supérieur et de la recherche*. Data for INSEE can be collected from this website.

Table A4 – Descriptive Statistics of Individual Characteristics in High School and Higher Education

	Treated				Control			
	Men		Women		Men		Women	
Second								
Age	15.51	0.85	15.43	0.82	15.49	0.82	15.41	0.83
Very High SES	0.21	0.41	0.20	0.40	0.22	0.41	0.20	0.40
Low SES	0.22	0.42	0.23	0.42	0.24	0.43	0.25	0.43
N	348267		349769		4440127		4533223	
Premiere								
Age	16.84	1.12	16.70	1.08	16.82	1.11	16.69	1.06
Very High SES	0.21	0.41	0.20	0.40	0.21	0.41	0.19	0.40
Low SES	0.23	0.42	0.23	0.42	0.25	0.43	0.25	0.44
N	354512		353970		4577734		4648005	
Terminale								
Age	17.71	1.00	17.58	0.95	17.70	0.99	17.56	0.93
Very High SES	0.26	0.44	0.23	0.42	0.25	0.44	0.23	0.42
Low SES	0.19	0.39	0.20	0.40	0.21	0.41	0.22	0.42
N	254999		276511		3336156		3654569	
Higher Education								
Age	20.43	2.14	20.41	2.15	20.46	2.20	20.31	2.14
Honors	2.02	0.99	2.03	1.00	2.00	0.98	2.00	0.99
Very High SES - Father	0.33	0.47	0.31	0.46	0.33	0.47	0.30	0.46
Low SES - Father	0.13	0.34	0.15	0.36	0.15	0.36	0.17	0.38
Very High SES - Mother	0.17	0.38	0.17	0.38	0.18	0.39	0.17	0.38
Low SES - Mother	0.04	0.20	0.04	0.20	0.04	0.20	0.05	0.21
N	2804		5222		41826		75895	

Notes : Descriptive statistics for educational choices variables using the BCS dataset, which contains information on high school students in France and the OVE data set historic, 2010, 2013, and 2016 waves, restricted to students between 17 and 35 years old, who graduated in metropolitan France, and who are enrolled in initial training. *Honors* refers to the grade at the high school graduation exam, with scores of 1 for above 10/20, 2 for above 12/20, 3 for above 14/20, and 4 for above 16/20. The CSP classification includes four broad categories : Very High SES (e.g., company managers, executives, liberal professions, engineers, academic and art professions), High SES (e.g., school teachers, nurses, administrative and commercial occupations), Medium SES (e.g., civil servants and public service employees, police and military personnel, company administrative and commercial employees), and Low SES (mainly blue-collar workers).

Table A5 – Descriptive Statistics for Track Choices in High School

	Treated				Control			
	Men		**Women**		**Men**		**Women**	
High School 1st Year								
Academic	0.63	0.48	0.72	0.45	0.63	0.48	0.72	0.45
Vocational - Baccalaureate Degree	0.28	0.45	0.21	0.41	0.29	0.45	0.22	0.41
Vocational - Non-Baccalaureate Degree	0.21	0.40	0.16	0.37	0.19	0.40	0.16	0.37
N	348267		349769		4440127		4533223	
High School 2nd Year								
Academic	0.37	0.48	0.47	0.50	0.37	0.48	0.47	0.50
Technologic	0.19	0.39	0.19	0.39	0.18	0.39	0.18	0.38
Vocational - Baccalaureate Degree	0.25	0.44	0.19	0.40	0.27	0.44	0.20	0.40
Vocational - Non-Baccalaureate Degree	0.19	0.39	0.15	0.36	0.18	0.38	0.15	0.36
N	354512		353970		4577734		4648005	
High School 3rd Year								
Academic	0.49	0.50	0.58	0.49	0.49	0.50	0.59	0.49
Technologic	0.23	0.42	0.24	0.43	0.22	0.41	0.24	0.43
Vocational - Baccalaureate Degree	0.25	0.43	0.17	0.38	0.25	0.43	0.17	0.38
Vocational - Non-Baccalaureate Degree	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01
N	254999		276511		3336156		3654569	

Notes : Descriptive statistics for educational choices variables using the BCS dataset, which contains information on high school students in France. All variables are dummy variables equal to one if the student is enrolled in a specific institution, field, or subfield.

Table A6 – Descriptive Statistics for Academic High School Choices

	Treated				**Control**			
	Men		**Women**		**Men**		**Women**	
Sciences	0.65	0.48	0.43	0.49	0.65	0.48	0.43	0.50
Humanities	0.08	0.26	0.23	0.42	0.07	0.26	0.22	0.42
Economics	0.28	0.45	0.35	0.48	0.27	0.45	0.34	0.47
N	130620		164820		1710579		2171537	

Notes : Descriptive statistics for educational choices variables using the BCS, which contains information on high school students in France. All variables are dummy variables equal to one if the student is enrolled in a specific institution, field, or subfield.

Table A7 – Descriptive Statistics for Higher Education Choices

	Treated				Control			
	Men		Women		Men		Women	
Fields								
Humanities and Social Sciences	0.13	0.33	0.26	0.44	0.12	0.32	0.26	0.44
Law and Economics	0.13	0.34	0.18	0.38	0.13	0.33	0.17	0.37
Science	0.15	0.36	0.10	0.30	0.16	0.37	0.11	0.31
Health	0.12	0.32	0.14	0.35	0.09	0.29	0.12	0.33
Tracks								
IUT	0.12	0.32	0.07	0.26	0.13	0.34	0.08	0.28
Advanced Vocational	0.07	0.26	0.06	0.23	0.08	0.27	0.07	0.26
Elite Preparatory	0.09	0.28	0.05	0.22	0.08	0.27	0.05	0.22
N	2804		5222		41826		75895	

Note : Descriptive statistics for educational choices variables using the OVE data set historic, 2010, 2013, and 2016 waves, restricted to students between 17 and 35 years old, who graduated in metropolitan France, and who are enrolled in initial training. All variables are dummy variables equal to 1 if the student is enrolled in a specific institution, field, or subfield.

Table A8 – ATT - Educational Choice in Higher Education - Not Yet Treated as Control Group

	Women		**Men**	
Math-Intensive	0.00394	0.0210***	0.0657***	0.0687***
	(0.00486)	(0.00327)	(0.0202)	(0.0201)
Unbiased Science	-0.00148	-0.0102*	0.0175*	0.00479
	(0.00576)	(0.00528)	(0.00926)	(0.0100)
N	81017	79525	44591	43790
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the OVE data set 2010, 2013, and 2016 and the historic waves restricted to students between 17 and 35 years old, who graduated in metropolitan France and are enrolled in initial training. The dependent variable is the likelihood of entering a certain track. Controls include age and parents' socio-economic category. Results are clustered at the county level, and weighted using the OVE's administrator weights. The control group is the not-yet-treated group.

Table A9 – ATT - Educational Choice in High School - Not Yet Treated as Control Group

	Women		Men	
Fields				
Computer Science	-0.00000151	0.000000601	0.0000882	0.0000836
	(0.00000775)	(0.00000909)	(0.0000648)	(0.0000587)
Math-Intensive	0.00431	0.00444*	0.0449***	0.0416***
	(0.00274)	(0.00259)	(0.0123)	(0.0112)
Unbiased Science	-0.0180***	-0.0152***	-0.0134*	-0.0126*
	(0.00512)	(0.00423)	(0.00755)	(0.00716)
N	1364023	1364023	1764163	1764163
Tracks				
Academic	-0.000414	-0.00367	-0.00735***	-0.00523**
	(0.00403)	(0.00228)	(0.00194)	(0.00219)
Vocational	-0.000587	0.00274	-0.0113*	-0.0130*
Baccalaureate Degree	(0.00496)	(0.00345)	(0.00622)	(0.00680)
Vocational	0.00996	0.00836***	0.0277***	0.0240*
Non-Baccalaureate Degree	(0.00862)	(0.00322)	(0.00774)	(0.0123)
N	4856050	4856050	4761437	4761437
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the BCS dataset, which contains information on high school students in France. The table shows results for students enrolled in their first year of high school as well as students in vocational tracks for the fields of study. The dependent variables are equal to one if the student is enrolled in a certain track or field in high school. Controls include age and socio-economic background. Results are clustered at the county level. The control group is the not-yet-treated group.

Table A10 – Ttest Treated and Control Groups - Pre-Programs

	Treated		Control		Diff	
	Mean	**SD**	**Mean**	**SD**	Diff	T
Individual Educational Characteristics (N= 42524)						
Sex (Student pop)	1.66	0.47	1.67	0.47	-0.01	(-0.993)
Age (Student pop)	20.69	2.50	20.78	2.49	-0.10	(-1.915)
Honors	1.72	0.86	1.73	0.86	-0.01	(-0.301)
Computer Science	0.05	0.21	0.03	0.18	0.01	(1.336)
Math intensive	0.09	0.29	0.09	0.29	0.00	(0.247)
Unbiased Science	0.06	0.24	0.06	0.24	-0.00	(-0.126)
Educational Characteristics (N= 282)						
Grad HS Success Women	82.55	4.93	82.77	4.29	0.22	(0.189)
Grad HS Success Men	78.51	4.41	78.59	4.62	0.07	(0.058)
Grad HS Success All	80.60	4.34	80.74	4.02	0.14	(0.132)
Technological Characteristics (N= 6216)						
Frequency at School	2.69	0.96	2.60	0.94	-0.10	(-0.863)
Frequency at Home	2.44	1.23	2.59	1.30	0.12	(0.885)
Frequency Internet at Home	4.47	1.02	4.22	1.26	-0.18	(-1.046)
School Availability Comp	0.74	0.44	0.81	0.39	0.07	(1.534)
Household Availability Comp	0.55	0.50	0.59	0.49	0.01	(0.583)
Household Availability Internet	0.35	0.48	0.34	0.48	0.00	(0.041)
Economic Characteristics (N= 3340454)						
Sexe (all pop)	1.45	0.50	1.46	0.50	0.01***	(6.919)
Age (all pop)	39.18	10.25	38.98	10.27	-0.09***	(-4.049)
Married	0.58	0.49	0.57	0.50	-0.02***	(-14.138)
No Diplom	0.11	0.31	0.10	0.30	-0.00**	(-2.978)
Pre-High School Diploma	0.48	0.50	0.48	0.50	-0.00	(-1.260)
High School Diploma	0.25	0.44	0.26	0.44	0.01***	(7.578)
Post-Bac Diploma	0.16	0.37	0.16	0.36	-0.00***	(-5.335)
Very High SES	0.13	0.33	0.14	0.34	0.01***	(10.783)
Low SES	0.24	0.43	0.24	0.43	-0.00***	(-3.876)
Unemployment	9.54	1.37	9.89	1.77	0.35	(0.759)

Notes : Test using the *Enquête Permanente sur les conditions de vie des ménages, partie variable : nouvelles technologies - octobre2001* from INSEE (weighted), the DEPP variable on success at the high school graduation exam, the Census data and unemployment from INSEE. The frequency of use questions are coded as 1 is every, 2 is at least once a week, 3 is several time months, 4 is once and 5 is never. For ownership questions : 1 is ownership and 2 is no ownership. Graduation in High School is the number of students who successfully passed the graduation exams over the number of students who took the exam. Unemployment is at the county level. Information about the socioeconomic background, as indicated by the occupation, are from the CSP classification : Very High SES (e.g., company managers, executives, liberal professions, engineers, academic and art professions) and Low SES (mainly blue-collar workers) are the main groups in France. Translations and classification are from Fack et al. (2019).

B.4 Results

Table A11 – ATT - Educational Choice in High School Track

	Women		Men	
	(1)	(2)	(3)	(4)
High School 2nd Year - Tracks				
Academic	-0.00390*	-0.000878	-0.000642	0.00267
	(0.00205)	(0.00290)	(0.00297)	(0.00439)
Technologic	-0.00251	0.000290	-0.00584***	-0.00356
	(0.00180)	(0.00336)	(0.00128)	(0.00377)
Vocational - Baccalaureate Degree	-0.00101	-0.00321	-0.0104***	-0.0116***
	(0.00507)	(0.00439)	(0.00352)	(0.00400)
Vocational - Non-Baccalaureate Degree	0.00738	0.00376	0.0168***	0.0125***
	(0.00604)	(0.00404)	(0.00380)	(0.00328)
N	4974283	4974283	4903511	4903511
High School 3rd Year - Tracks				
Academic	-0.00968	-0.00916*	-0.00890	-0.00881**
	(0.00800)	(0.00537)	(0.00689)	(0.00389)
Technologic	0.0123***	0.0132***	0.0127**	0.0116**
	(0.00317)	(0.00187)	(0.00638)	(0.00495)
Vocational - Baccalaureate Degree	-0.00189	-0.00336	-0.00593	-0.00529
	(0.00590)	(0.00545)	(0.00390)	(0.00440)
Vocational - Non-Baccalaureate Degree	-0.000681	-0.000614	-0.000509	-0.000540
	(0.00105)	(0.000974)	(0.000891)	(0.000930)
N	3931080	3931080	3591155	3591155
High School 2nd Year - Fields				
Computer Science	0.00000247	0.00000467	0.0000614	0.0000676
	(0.00000433)	(0.00000599)	(0.0000433)	(0.0000454)
Math-intensive	0.00284**	0.00217	0.0216	0.0269**
	(0.00138)	(0.00165)	(0.0143)	(0.0125)
Unbiased Science	-0.00178*	-0.000611	-0.00538	-0.00453
	(0.00100)	(0.000993)	(0.00647)	(0.00478)
N	1742166	1742166	2179587	2179587
High School 3rd Year - Fields				
Computer Science	-0.0000583	-0.0000626	0.00378	0.00338
	(0.0000583)	(0.0000638)	(0.00482)	(0.00425)
Math-intensive	0.00268	0.00434	0.0280	0.0448**
	(0.00625)	(0.00405)	(0.0202)	(0.0191)
Unbiased Science	-0.00569	-0.00328	-0.00936	-0.0105*
	(0.00426)	(0.00354)	(0.00633)	(0.00555)
N	682931	682931	899502	899502
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the BCS dataset, which contains information on high school students in France. The table shows results for students enrolled in their second and third year of high school of the tracks (*Première* and *Terminale*) as well as students in vocational tracks for the fields of study. The dependent variables are equal to one if the student is enrolled in a certain track or field in high school. Controls include age and socio-economic background. Results are clustered at the county level.

Table A12 – ATT - Education Choice in Academic Fields High School Specialization

	Women		**Men**	
	(1)	(2)	(3)	(4)
Science	-0.00212	0.000239	0.0148*	0.0157
	(0.00503)	(0.00658)	(0.00800)	(0.00962)
Economics and Social Sciences	0.00588	0.00418	-0.00565	-0.00728
	(0.00626)	(0.00708)	(0.00678)	(0.00793)
Humanities	-0.00376*	-0.00442***	-0.00919***	-0.00846***
	(0.00199)	(0.00153)	(0.00161)	(0.00193)
N	2323838	2323838	1831710	1831710
Controls	No	Yes	No	Yes

Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the Base Centrale Scolarité dataset, which contains information on high school students in France restricted to students enrolled in the academic track during their second year of high school. The dependent variables are equal to one if the student is enrolled in a certani specialization in high school. Controls include age and socio-economic background. Results are clustered at the county level.

Table A13 – ATT - Educational Choice in High School - TWFE Interaction

	Computer Science		**Math-Intensive**		**Unbiased Science**	
Treated × Women	-0.000136	-0.000136	0.00840	0.00930	-0.00124	-0.00113
	(0.000158)	(0.000158)	(0.0127)	(0.0130)	(0.00145)	(0.00139)
Women	-0.0000104	-0.0000104	-0.221***	-0.218***	-0.00596***	-0.00536***
	(0.00000733)	(0.00000731)	(0.00693)	(0.00705)	(0.000385)	(0.000394)
Treated	0.0000922	0.0000923	0.00211	0.00297	-0.00261	-0.00249
	(0.0000861)	(0.0000862)	(0.00776)	(0.00787)	(0.00182)	(0.00168)
N	9671386	9671386	9671386	9671386	9671386	9671386
Controls	No	Yes	No	Yes	No	Yes

Notes : Standard errors in parenthesis. I report estimates from an OLS methodology. I use the OVE data set 2010, 2013, and 2016 and the historic waves restricted to students between 17 and 35 years old, who graduated in metropolitan France and are enrolled in initial training. The dependent variable is the likelihood of entering a certain field. Controls include age and parents' socio-economic category. Results are clustered at the county level, and weighted using the OVE's administrator weights.

Table A14 – ATT - Educational Choice in Higher Education - TWFE Interaction

	Math-Intensive		**Unbiased Science**	
Treated × Women	0.0108	0.0102	0.00847	0.00921
	(0.00922)	(0.00950)	(0.00935)	(0.00901)
Women	-0.119***	-0.118***	0.00556***	0.00551***
	(0.00272)	(0.00266)	(0.00190)	(0.00194)
Treated	0.00389	0.00206	-0.0164*	-0.0184*
	(0.0118)	(0.0111)	(0.00911)	(0.00967)
N	125608	123430	125608	123430
R^2	0.047	0.050	0.004	0.006
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. I report estimates from an OLS methodology. I use the OVE data set 2010, 2013, and 2016 and the historic waves restricted to students between 17 and 35 years old, who graduated in metropolitan France and are enrolled in initial training. The dependent variable is the likelihood of entering a certain field. Controls include age and parents' socio-economic category. Results are clustered at the county level, and weighted using the OVE's administrator weights.

Table A15 – ATT - Education Choices in Higher Education - Only the Last Three Waves

	Women		Men	
Main Results				
Computer Science	0.000864	0.000159	0.0530***	0.0424***
	(0.00484)	(0.00460)	(0.00530)	(0.0111)
Math-Intensive	0.0109	0.0367**	0.0705***	0.0570**
	(0.00797)	(0.0167)	(0.0170)	(0.0230)
Unbiased Science	0.00419	-0.00373	0.0162*	0.00723
	(0.00664)	(0.00494)	(0.00904)	(0.0136)
N	58893	58817	33648	33331
Fields				
Humanities	-0.0456**	-0.0595***	-0.00232	-0.0420
	(0.0192)	(0.00734)	(0.0226)	(0.0490)
Social Sciences	0.00312	0.0204	0.0186	0.0114
	(0.0211)	(0.0455)	(0.0299)	(0.0490)
Teaching	0.0171***	0.0183**	0.00780	0.00682
	(0.00343)	(0.00914)	(0.00548)	(0.00657)
Law	0.00110	-0.0574	0.0113	0.00426
	(0.00867)	(0.0655)	(0.00905)	(0.0111)
Economics	0.0691	0.0875	0.0394	0.0704**
	(0.0572)	(0.0732)	(0.0330)	(0.0318)
Science	-0.00372	0.0155	-0.105	-0.0731
	(0.0137)	(0.0245)	(0.0892)	(0.111)
Health	-0.0515	-0.0329	0.0136	-0.00340
	(0.0432)	(0.0457)	(0.0342)	(0.0265)
N	58476	58401	33481	33164
University	-0.0280	-0.0266	0.106	0.0790
	(0.0638)	(0.0579)	(0.120)	(0.133)
Preparatory Elite	-0.0554	-0.0572	-0.0475	-0.0209
	(0.0513)	(0.0444)	(0.0308)	(0.0446)
Advanced Vocational	0.0243***	0.0438***	-0.101	-0.0720
	(0.00708)	(0.0102)	(0.0877)	(0.0644)
Engineering School	0.0211***	0.0280**	0.0179	-0.00459
	(0.00790)	(0.0119)	(0.0254)	(0.0426)
Business School	0.0356*	0.00586	0.0296***	0.0107
	(0.0188)	(0.0197)	(0.00619)	(0.0101)
Art School	0.00177	0.00545	-0.00548	0.00778***
	(0.00943)	(0.0147)	(0.00469)	(0.00218)
N	58297	58221	33589	33273
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the OVE data set 2010, 2013, and 2016 restricted to students between 17 and 35 years old, who graduated in metropolitan France and are enrolled in initial training. The dependent variables are variables equal to one of entering a certain field and track. Controls include age and parents' socio-economic category. Results are clustered at the county level, and weighted using the OVE's administrator weights.

Table A16 – ATT - Educational Choice in Higher Education - TWFE Interaction

	Math-Intensive		**Unbiased Science**	
Treated × Women	0.0108	0.0102	0.00847	0.00921
	(0.00922)	(0.00950)	(0.00935)	(0.00901)
Women	-0.119***	-0.118***	0.00556***	0.00551***
	(0.00272)	(0.00266)	(0.00190)	(0.00194)
Treated	0.00389	0.00206	-0.0164*	-0.0184*
	(0.0118)	(0.0111)	(0.00911)	(0.00967)
N	125608	123430	125608	123430
R^2	0.047	0.050	0.004	0.006
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. I report estimates from an OLS methodology. I use the OVE data set 2010, 2013, and 2016 and the historic waves restricted to students between 17 and 35 years old, who graduated in metropolitan France and are enrolled in initial training. The dependent variable is the likelihood of entering a certain field. Controls include age and parents' socio-economic category. Results are clustered at the county level, and weighted using the OVE's administrator weights.

Table A17 – ATT - Education Choices in Higher Education - All Gender

	(1)	(2)
Main Results		
Math-Intensive	0.0296***	0.0284**
	(0.0111)	(0.0136)
Unbiased Science	0.00977	0.00186
	(0.00605)	(0.00638)
N	125608	123315
Field		
Humanities and Social Sciences	-0.00875	-0.0416
	(0.0443)	(0.0567)
Law and Economics	0.00830	-0.0000563
	(0.0140)	(0.00712)
Science	0.0356***	0.0332**
	(0.0103)	(0.0136)
Health	-0.0153	-0.0152
	(0.0358)	(0.0362)
IUT	-0.00529	0.0228
	(0.0140)	(0.0315)
Advanced Vocational	-0.0282	0.00285
	(0.0536)	(0.0470)
Elite Preparatory	-0.0514	-0.0352
	(0.0378)	(0.0433)
N	125593	123302
Controls	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the OVE data set 2010, 2013, and 2016 and the historic waves restricted to students between 17 and 35 years old, who graduated in metropolitan France and are enrolled in initial training. The dependent variable is the likelihood of entering a certain field or track. Controls include age and parents' socio-economic category. Results are clustered at the county level, and weighted using the OVE's administrator weights.

Table A18 – ATT - Share of Workers in Alternative Math-Intensive Profession and Industry at the County Level - EE

	Profession		**Industry**	
	Women	**Men**	**Women**	**Men**
	(1)	(2)	(3)	(4)
Computer Science	0.00313**	-0.00663	-0.00256	0.00102
	(0.00139)	(0.00862)	(0.00361)	(0.00306)
Math-intensive	0.0109**	-0.0341*	-0.00916	-0.00234
	(0.00556)	(0.0192)	(0.00830)	(0.0154)
Math-intensive Alternative	0.0189**	0.00825	0.000522	0.0366**
	(0.00769)	(0.0200)	(0.0120)	(0.0173)
Unbiased Science	0.00564	0.0157	0.00830	-0.00555
	(0.0176)	(0.00959)	(0.0134)	(0.0108)
N	2088	2089	2088	2089
Controls	No	No	No	No

Notes : tandard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. The data comes from the *Enquête Emploi*, and I restrict the sample to men aged 15 and older who are currently employed. I construct a panel dataset at the county level covering the years 1984 to 2015. The dependent variables of interest are the likelihood of working in an industry related to mathematics or computer science or having an occupation related to these fields. Results are clustered at the county level.

Table A19 – ATT - Geographical Choice of Study in Higher Education

	Women		**Men**	
	(1)	(2)	(3)	(4)
County Level	0.0640***	0.0422	0.109***	0.172***
	(0.0221)	(0.0276)	(0.0184)	(0.0200)
Academy Level	0.0249	0.00821	0.0806*	0.102**
	(0.0168)	(0.0272)	(0.0480)	(0.0517)
N	80965	79473	44560	43719
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the OVE data set 2010, 2013, and 2016 restricted to students between 17 and 35 years old, who graduated in metropolitan France, and are enrolled in initial training. The dependent variable is a dummy equal to one if the student is enrolled in a higher education institution that is not in the same county as the county of high school graduation (*County Level*) and or not in the same Academy (*Academy Level*), an administrative division of the Ministry of National Education and the Ministry of Higher Education and Research. Controls include age, honors at the high school graduation exam, and father's socio-economic category. Results are clustered at the county level.

Table A20 – ATT - Educational Choice in High School - Heterogeneity Parents SES

	Women		Men	
	Above	**Below**	**Above**	**Below**
Fields				
Computer Science	-0.0000827	0.00000537	0.000123	0.0000749
	(0.0000572)	(0.00000873)	(0.0000961)	(0.0000541)
Math-Intensive	0.00354	0.00459**	0.0353***	0.0487***
	(0.00598)	(0.00232)	(0.00891)	(0.0155)
Unbiased Science	-0.00215	-0.0224***	0.00255	-0.0197**
	(0.00828)	(0.00413)	(0.00640)	(0.00775)
N	318076	1045947	476283	1287880
Tracks				
Academic	-0.00854**	0.00360	-0.000258	-0.0132***
	(0.00355)	(0.00711)	(0.00163)	(0.00357)
Vocational	0.00479**	-0.00361	-0.00583**	-0.0171*
Baccalaureate Degree	(0.00193)	(0.00951)	(0.00289)	(0.00993)
Vocational	0.0151***	0.00311	0.0113**	0.0373***
Non-Baccalaureate Degree	(0.00358)	(0.0110)	(0.00465)	(0.0112)
N	2147931	2708119	2195891	2565546
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the BCS dataset, which contains information on high school students in France. The table shows results for students enrolled in their first year of high school of the tracks as well as students in vocational tracks for the fields of study. The dependent variables are equal to one if the student is enrolled in a certain track or field in high school. Results are clustered at the county level. *Above* means that the student's background is in a SES category, defined in section A1, above the average income of the parents in the sample.

Table A21 – ATT - Educational Choice in Higher Education - Heterogeneity Parents SES

	Women		**Men**	
	Above	**Below**	**Above**	**Below**
Math-Intensive	-0.0102	0.0179	0.0670	0.0284
	(0.00747)	(0.0137)	(0.0517)	(0.0249)
Unbiased Science	0.00401	-0.0233	0.0155	0.0159
	(0.0178)	(0.0368)	(0.0104)	(0.0148)
N	47840	29714	27834	14863
Controls	Yes	Yes	Yes	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the OVE data set 2010, 2013, and 2016 and the historic waves restricted to students between 17 and 35 years old, who graduated in metropolitan France and are enrolled in initial training. The dependent variable is the likelihood of entering a certain track. Controls include age and parents' socio-economic category. Results are clustered at the county level, and weighted using the OVE's administrator weights. *Above* means that the student's background is in a SES category, defined in section A1, above the average income of the parents in the sample.

B.5 Robustness

Table A22 – ATT - Educational Choice in High School - Only Leftist County

	Women				Men			
	Always	2001	2004	2008	Always	2001	2004	2008
Fields								
Math-Intensive	0.00354	0.00503	-0.000656	0.00493	0.0402***	0.0341***	0.0311***	0.0511***
	(0.00328)	(0.00422)	(0.00243)	(0.00388)	(0.0118)	(0.0120)	(0.0110)	(0.0154)
Unbiased Science	-0.0147***	-0.0114*	-0.0201***	-0.0122**	-0.0118*	-0.00634	-0.0136*	-0.00902
	(0.00460)	(0.00659)	(0.00456)	(0.00584)	(0.00692)	(0.00914)	(0.00793)	(0.00803)
N	576960	129497	230049	180049	749216	182026	298918	228998
Tracks								
Academic	-0.00501*	0.00578	0.00336	-0.00549*	-0.00551	0.00129	-0.000811	-0.00698*
	(0.00303)	(0.00437)	(0.00476)	(0.00308)	(0.00434)	(0.00426)	(0.00356)	(0.00393)
Vocational	0.00156	0.00649	0.00182	0.00276	-0.0171*	0.0000954	-0.00749	-0.0101
Baccalaureate Degree	(0.00414)	(0.00717)	(0.00508)	(0.00516)	(0.00911)	(0.00619)	(0.00715)	(0.00695)
Vocational	0.0155***	-0.00689**	-0.000682	0.00779**	0.0302**	0.00548	0.0177	0.0200*
Non-Baccalaureate Degree	(0.00572)	(0.00289)	(0.00293)	(0.00386)	(0.0136)	(0.0109)	(0.0110)	(0.0114)
N	1924393	517421	827639	640623	1914452	510543	811536	628463
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the BCS dataset, which contains information on high school students in France. The table shows results for students enrolled in their first year of high school of the tracks as well as students in vocational tracks for the fields of study. The dependent variables are equal to one if the student is enrolled in a certain track or field in high school. Controls include age and socio-economic background. Results are clustered at the county level. The dates mentioned on top refer to the election dates. In each pair of columns, the control group consists of only leftist counties and switchers during that specific election and treatment are the usual treated counties with a program. For example, in the 2001 column, the treated counties are included and the control group comprises all the leftist counties following the 2001 election. Results are clustered at the county level.

Table A23 – ATT - Educational Choice in Higher Education - Only Leftist County

	Always		**2001**		**2004**		**2008**	
	Women	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**
Math-Intensive	0.0159*	0.0566***	0.0240***	0.0399	0.0395***	0.0704*	0.0170***	0.133***
	(0.00855)	(0.0205)	(0.00600)	(0.0443)	(0.00911)	(0.0424)	(0.00637)	(0.0383)
Unbiased science	-0.0126*	0.00319	-0.0125	0.0189	-0.0190	0.00766	-0.0174*	0.0120
	(0.00749)	(0.0138)	(0.0105)	(0.0262)	(0.0116)	(0.0102)	(0.00977)	(0.0119)
N	29674	15779	7417	3377	12885	7019	9808	4827

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the OVE data set 2010, 2013, and 2016 and the historic waves restricted to students between 17 and 35 years old, who graduated in metropolitan France and are enrolled in initial training. The dependent variable is the likelihood of entering a certain track. Controls include age and parents' socio-economic category. Results are clustered at the county level, and weighted using the OVE's administrator weights. The dates mentioned on top refer to the election dates. In each pair of columns, the control group consists of only leftist counties and switchers during that specific election and treatment are the usual treated counties with a program. For example, in the 2001 column, the treated counties are included and the control group comprises all the leftist counties following the 2001 election.

Table A24 – ATT - Educational Choice in High School - Control for Proximity to Public Higher Education Institutions

	Women		Men	
Fields				
Computer Science	-0.0000128	-0.00000576	0.000302	0.000226
	(0.0000199)	(0.0000140)	(0.000331)	(0.000244)
Math-Intensive	0.00364	0.00372	0.0332***	0.0299***
	(0.00316)	(0.00312)	(0.00630)	(0.00609)
Unbiased Science	-0.0147***	-0.0126***	-0.0133*	-0.00909*
	(0.00373)	(0.00309)	(0.00736)	(0.00514)
N	1364023	1364023	1764163	1764163
Tracks				
Academic	0.00905	0.000108	0.000871	0.00339
	(0.00857)	(0.00473)	(0.00465)	(0.00763)
Vocational	-0.00325	0.00573	-0.0171*	-0.0189*
Baccalaureate Degree	(0.00623)	(0.00380)	(0.00940)	(0.0109)
Vocational	-0.00223	0.00368	0.0152*	0.0139
Non-Baccalaureate Degree	(0.0174)	(0.00686)	(0.00810)	(0.00866)
N	4856050	4856050	4761437	4761437
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the BCS dataset, which contains information on high school students in France. The table shows results for students enrolled in their first year of high school of the tracks as well as students in vocational tracks for the fields of study. The dependent variables are equal to one if the student is enrolled in a certain track or field in high school. Controls include age and socio-economic background. Results are clustered at the county level. I control for the proximity to higher education institutions using data from Open Data MESR - *Principaux établissements d'enseignement supérieur*. I use GPS coordinates of all cities in the county to find an average and use it to calculate the centrality of the county to all post-secondary institutions. Results are clustered at the county level.

Table A25 – ATT - Educational Choice in Higher Education - Control for Proximity to Higher Education Institutions

	Treated		Control	
	Women	**Men**	**Women**	**Men**
Math-Intensive	0.000534	0.0167	0.0831***	0.0995***
	(0.0111)	(0.0104)	(0.0306)	(0.0245)
Math-Intensive 2	0.00265	0.0179*	0.0798***	0.0964***
	(0.00988)	(0.00933)	(0.0250)	(0.0251)
Unbiased Science	0.00280	-0.000147	0.00851	-0.00398
	(0.00744)	(0.0125)	(0.0162)	(0.0153)
Unbiased Science 2	0.00332	-0.000967	0.0118	-0.000824
	(0.00784)	(0.0112)	(0.0145)	(0.0134)
N	81017	79525	44591	43750

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the OVE data set 2010, 2013, and 2016 and the historic waves restricted to students between 17 and 35 years old, who graduated in metropolitan France and are enrolled in initial training. The dependent variable is the likelihood of entering a certain field. Controls include age and parents' socio-economic category. Results are clustered at the county level, and weighted using the OVE's administrator weights. I control for the proximity to higher education institutions using data from Open Data MESR - *Principaux établissements d'enseignement supérieur* - Variable (1), and using hand-collected data on post-secondary education offering computer science diplomas - Variables (2) I use GPS coordinates of all cities in the county to find an average and use it to calculate the centrality of the county to all post-secondary institutions. Results are clustered at the county level.

Table A26 – ATT - Educational Choice in High School - Control for Proximity to Computer Science Institutions

	Women		Men	
Fields				
Computer Science	-0.0000152	-0.00000622	0.000360	0.000267
	(0.0000261)	(0.0000180)	(0.000400)	(0.000297)
Math-Intensive	0.00344	0.00378	0.0362***	0.0324***
	(0.00268)	(0.00265)	(0.00728)	(0.00668)
Unbiased Science	-0.0153***	-0.0131***	-0.0131*	-0.00966*
	(0.00351)	(0.00287)	(0.00698)	(0.00511)
N	1364023	1364023	1764163	1764163
Tracks				
Academic	0.00782	-0.000466	-0.000723	0.00156
	(0.00730)	(0.00418)	(0.00417)	(0.00658)
Vocational	-0.00328	0.00486	-0.0161*	-0.0178*
Baccalaureate Degree	(0.00642)	(0.00362)	(0.00926)	(0.0106)
Vocational	-0.000459	0.00428	0.0192***	0.0176**
Non-Baccalaureate Degree	(0.0161)	(0.00575)	(0.00645)	(0.00739)
N	4856050	4856050	4761437	4761437
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the BCS dataset, which contains information on high school students in France. The table shows results for students enrolled in their first year of high school of the tracks as well as students in vocational tracks for the fields of study. The dependent variables are equal to one if the student is enrolled in a certain track or field in high school. Controls include age and socio-economic background. Results are clustered at the county level. I control for the proximity to higher education institutions using hand-collected data on post-secondary education offering computer science diplomas - Variables (2) I use GPS coordinates of all cities in the county to find an average and use it to calculate the centrality of the county to all post-secondary institutions. Results are clustered at the county level.

Table A27 – ATT - Educational Choice in High School - Control for Broadband Access in the County - Type 1

	Women		Men	
Fields				
Computer Science	0.00000210	0.00000372	0.0000515	0.0000526
	(0.00000597)	(0.00000739)	(0.0000324)	(0.0000375)
Math-Intensive	0.00488	0.00463	0.0402***	0.0369***
	(0.00354)	(0.00319)	(0.0113)	(0.0109)
Unbiased Science	-0.0158***	-0.0137***	-0.0113	-0.0106
	(0.00435)	(0.00386)	(0.00691)	(0.00664)
N	1358578	1358578	1757531	1757531
Tracks				
Academic	-0.00153	-0.00395*	-0.00807***	-0.00187
	(0.00384)	(0.00237)	(0.00274)	(0.00386)
Vocational	-0.00184	0.000659	-0.0138*	-0.0187*
Baccalaureate Degree	(0.00569)	(0.00471)	(0.00795)	(0.0105)
Vocational	0.00890	0.00783**	0.0190***	0.0158**
Non-Baccalaureate Degree	(0.0104)	(0.00317)	(0.00660)	(0.00717)
N	4835731	4835731	4742039	4742039
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the BCS dataset, which contains information on high school students in France. The table shows results for students enrolled in their first year of high school of the tracks as well as students in vocational tracks for the fields of study. The dependent variables are equal to one if the student is enrolled in a certain track or field in high school. Controls include age and socio-economic background and the average year of broadband access in the county, using broadband access data from Malgouyres et al. (2021). Refer to Malgouyres et al. (2021) for details on methods for weighting in type 1 or 2. Results are clustered at the county level.

Table A28 – ATT - Educational Choice in High School - Control for Broadband Access in the County - Type 2

	Women		Men	
Fields				
Computer Science	0.00000326	0.00000508	0.0000701	0.0000670
	(0.00000836)	(0.0000101)	(0.0000453)	(0.0000466)
Math-Intensive	0.00400	0.00397	0.0415***	0.0379***
	(0.00288)	(0.00268)	(0.0104)	(0.00940)
Unbiased Science	-0.0164***	-0.0140***	-0.0118*	-0.0110*
	(0.00452)	(0.00383)	(0.00641)	(0.00609)
N	1358578	1358578	1757531	1757531
Tracks				
Academic	-0.00153	-0.00395*	-0.00689***	-0.00350
	(0.00384)	(0.00237)	(0.00224)	(0.00304)
Vocational	-0.00184	0.000659	-0.0130*	-0.0162*
	(0.00569)	(0.00471)	(0.00762)	(0.00941)
Vocational	0.00890	0.00783**	0.0243***	0.0206**
	(0.0104)	(0.00317)	(0.00652)	(0.00820)
N	4835731	4835731	4742039	4742039
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the BCS dataset, which contains information on high school students in France. The table shows results for students enrolled in their first year of high school of the tracks as well as students in vocational tracks for the fields of study. The dependent variables are equal to one if the student is enrolled in a certain track or field in high school. Controls include age and socio-economic background and the average year of broadband access in the county, using broadband access data from Malgouyres et al. (2021). Refer to Malgouyres et al. (2021) for details on methods for weighting in type 1 or 2. Results are clustered at the county level.

Table A29 – ATT - Educational Choice in Higher Education - Control for Broadband Access in the County

	Women		**Men**	
Math-Intensive	-0.00311	0.00966	0.0654***	0.0743***
	(0.00978)	(0.00998)	(0.0224)	(0.0190)
Math-Intensive 2	0.000342	0.0144**	0.0692***	0.0752***
	(0.00740)	(0.00620)	(0.0240)	(0.0256)
Unbiased Science	-0.00116	-0.00989*	0.0123	-0.000358
	(0.00604)	(0.00599)	(0.0110)	(0.0120)
Unbiased Science 2	-0.00123	-0.0111**	0.0135	0.00119
	(0.00526)	(0.00554)	(0.0104)	(0.0114)
N	80728	79239	44445	43605

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the OVE data set 2010, 2013, and 2016 and the historic waves restricted to students between 17 and 35 years old, who graduated in metropolitan France and are enrolled in initial training. The dependent variable is the likelihood of entering a certain field. Controls include age and parents' socio-economic category and the average year of broadband access in the county, using broadband access data from Malgouyres et al. (2021). Results are clustered at the county level, and weighted using the OVE's administrator weights.

Table A30 – ATT - Educational Choice in High School - Control Group Restricted to *régions*

	Women		Men	
Fields				
Computer Science	-0.0000107	-0.000000445	0.000577	0.000546
	(0.0000521)	(0.0000557)	(0.000409)	(0.000369)
Math-Intensive	0.00711	0.00729	0.0407***	0.0382***
	(0.00458)	(0.00472)	(0.0116)	(0.0111)
Unbiased Science	-0.0120**	-0.00884**	-0.0132*	-0.0123
	(0.00494)	(0.00413)	(0.00747)	(0.00747)
N	287523	287523	376961	376961
Tracks				
Academic	0.00390	-0.00124	-0.00120	-0.000637
	(0.00471)	(0.00307)	(0.00279)	(0.00351)
Vocational	-0.00315	0.00232	-0.0145**	-0.0143**
Baccalaureate Degree	(0.00548)	(0.00357)	(0.00715)	(0.00650)
Vocational	0.00712	0.0120**	0.0286***	0.0328***
Non-Baccalaureate Degree	(0.00982)	(0.00567)	(0.00693)	(0.0123)
N	1030102	1030102	1015539	1015539
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the BCS dataset, which contains information on high school students in France. The table shows results for students enrolled in their first year of high school of the tracks as well as students in vocational tracks for the fields of study. The dependent variables are equal to one if the student is enrolled in a certain track or field in high school. Controls include age and socio-economic background. Results are clustered at the county level. The control group is restricted to counties in the same *région* as the treated counties.

Table A31 – ATT - Educational Choice in Higher Education - Control Group Restricted to *régions*

	Women		**Men**	
Math-Intensive	0.00422	0.0219***	0.0460**	0.0568*
	(0.00858)	(0.00699)	(0.0202)	(0.0319)
Unbiased Science	-0.00187	-0.0114	0.00482	-0.0103
	(0.00602)	(0.00710)	(0.0178)	(0.0178)
N	15975	15442	8603	8037
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the OVE data set 2010, 2013, and 2016 and the historic waves restricted to students between 17 and 35 years old, who graduated in metropolitan France and are enrolled in initial training. The dependent variable is the likelihood of entering a certain field. Controls include age and parents' socio-economic category. Results are clustered at the county level, and weighted using the OVE's administrator weights. The control group is restricted to counties in the same *région* as the treated counties.

Table A32 – ATT - Educational Choice in High School - TWFE

	Women		Men	
Fields				
Computer Science	0.00000708	0.00000709	0.000121	0.000121
	(0.00000660)	(0.00000670)	(0.0000774)	(0.0000780)
Math-Intensive	0.00163	0.00195	0.0233	0.0221
	(0.00312)	(0.00321)	(0.0143)	(0.0134)
Unbiased Science	-0.0121***	-0.0119***	-0.00870	-0.00860
	(0.00292)	(0.00278)	(0.00610)	(0.00602)
N	1372234	1372234	0.000109	0.000203
Tracks				
Academic	-0.000800	-0.00585	-0.00551	-0.00841*
	(0.00651)	(0.00519)	(0.00426)	(0.00447)
Vocational	-0.00235	0.000871	-0.00706	-0.00517
Baccalaureate Degree	(0.00700)	(0.00621)	(0.00458)	(0.00516)
Vocational	0.00595	0.00928	0.0193	0.0211
Non-Baccalaureate Degree	(0.0124)	(0.0114)	(0.0124)	(0.0128)
N	4788394	4788394	4882992	4882992
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. Notes : Standard errors in parenthesis. I report estimates from an OLS methodology. I use the BCS dataset, which contains information on high school students in France. The table shows results for students enrolled in their first year of high school of the tracks as well as students in vocational tracks for the fields of study. The dependent variables are equal to one if the student is enrolled in a certain track or field in high school. Controls include age and socio-economic background. Results are clustered at the county level.

Table A33 – ATT - Educational Choice in Higher Education - TWFE

	Women		**Men**	
Math-Intensive	-0.0000163	-0.00000882	0.0208	0.0142
	(0.00496)	(0.00522)	(0.0166)	(0.0161)
Unbiased Science	-0.00817**	-0.00864**	-0.0161*	-0.0195*
	(0.00344)	(0.00347)	(0.00969)	(0.00984)
N	81017	79601	44591	43829
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. I report estimates from an OLS methodology. I use the OVE data set 2010, 2013, and 2016 and the historic waves restricted to students between 17 and 35 years old, who graduated in metropolitan France and are enrolled in initial training. The dependent variable is the likelihood of entering a certain track. Controls include age and parents' socio-economic category. Results are clustered at the county level, and weighted using the OVE's administrator weights.

Table A34 – ATT - Educational Choice in High School - Excluding Oise and Corrèze

	Women		Men	
Fields				
Computer Science	-0.00000163	-0.000000249	0.0000891	0.0000889
	(0.00000788)	(0.00000838)	(0.0000655)	(0.0000628)
Math-Intensive	0.00546**	0.00565**	0.0536***	0.0516***
	(0.00234)	(0.00236)	(0.00741)	(0.00674)
Unbiased Science	-0.0209***	-0.0175***	-0.0158**	-0.0148*
	(0.00418)	(0.00371)	(0.00761)	(0.00773)
N	1336673	1336673	1730353	1730353
Tracks				
Academic	-0.00392	-0.00744***	-0.00900***	-0.00813***
	(0.00321)	(0.00175)	(0.00156)	(0.00211)
Vocational	0.00166	0.00556*	-0.0133**	-0.0138***
Baccalaureate Degree	(0.00584)	(0.00324)	(0.00622)	(0.00519)
Vocational	0.0127	0.0153***	0.0328***	0.0348**
Non-Baccalaureate Degree	(0.0103)	(0.00390)	(0.00610)	(0.0141)
N	4767887	4767887	4676567	4676567
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. Notes : Standard errors in parenthesis. I report estimates from an OLS methodology. I use the BCS dataset, which contains information on high school students in France. The table shows results for students enrolled in their first year of high school of the tracks as well as students in vocational tracks for the fields of study. The dependent variables are equal to one if the student is enrolled in a certain track or field in high school. Controls include age and socio-economic background. Results are clustered at the county level. Oise and Corrèze are excluded from the analysis.

Table A35 – ATT - Educational Choice in Higher Education - Excluding Oise and Corrèze

	Women		**Men**	
Math-Intensive	0.00741*	0.0211***	0.0682***	0.0687***
	(0.00379)	(0.00334)	(0.0202)	(0.0200)
Unbiased Science	-0.00324	-0.0107**	0.0170*	0.00468
	(0.00605)	(0.00535)	(0.00943)	(0.0101)
N	79193	77792	43575	42826
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the OVE data set 2010, 2013, and 2016 and the historic waves restricted to students between 17 and 35 years old, who graduated in metropolitan France and are enrolled in initial training. The dependent variable is the likelihood of entering a certain track. Controls include age and parents' socio-economic category. Results are clustered at the county level, and weighted using the OVE's administrator weights. Oise and Corrèze are excluded from the analysis.

Table A36 – ATT - Educational Choice in Higher Education - Unweighted

	Women		Men	
Subfields				
Math-Intensive	0.0278***	0.0321***	0.0998***	0.101***
	(0.00593)	(0.00602)	(0.0284)	(0.0189)
Unbiased Science	0.0149	-0.00971	0.0374**	0.0183
	(0.0164)	(0.0177)	(0.0146)	(0.0229)
Fields				
Humanities and Social Sciences	-0.0366	-0.0211	-0.00471	-0.0194
	(0.0533)	(0.0480)	(0.0333)	(0.0464)
Law and Economics	-0.00361	-0.0234	-0.0116	-0.0293
	(0.0149)	(0.0192)	(0.0135)	(0.0202)
Science	0.0159	-0.00527	0.0598***	0.0588***
	(0.0241)	(0.0268)	(0.00895)	(0.0168)
Health	-0.0542***	-0.0442***	-0.000570	-0.00452
	(0.0150)	(0.0167)	(0.0194)	(0.0167)
Tracks				
IUT	-0.00742	0.00901	-0.0705***	-0.0376
	(0.0130)	(0.0141)	(0.0258)	(0.0432)
Advanced Vocational	0.0137	0.0251***	-0.0479	-0.0448
	(0.0123)	(0.00583)	(0.0546)	(0.0363)
Elite Preparatory	-0.0204	-0.00423	-0.0352**	0.00315
	(0.0217)	(0.0204)	(0.0170)	(0.0217)
N	81008	79453	44585	43711
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the OVE data set 2010, 2013, and 2016 and the historic waves restricted to students between 17 and 35 years old, who graduated in metropolitan France and are enrolled in initial training. The dependent variable is the likelihood of entering a certain track. Controls include age and parents' socio-economic category. Results are clustered at the county level. Year 3 and Year 4 refer to the timing used to defined treatment : 3 years prior to the actual treatment or 4 years prior to the treatment.

Table A37 – ATT - Educational Choice in High School - Geographical Placebo

	Women		Men	
Fields				
Computer Science	0.00000406	0.00000905	0.0000934	0.000111
	(0.00000760)	(0.0000117)	(0.0000666)	(0.0000824)
Math-Intensive	-0.00738	-0.00663	0.0142	0.0140
	(0.00586)	(0.00576)	(0.00950)	(0.00881)
Unbiased Science	-0.00234	-0.00135	0.00557	0.00594
	(0.00531)	(0.00566)	(0.00426)	(0.00447)
N	1359170	1359170	1758665	1758665
Tracks				
Academic	-0.00255	-0.00449	-0.00380	-0.00850
	(0.00331)	(0.00624)	(0.00923)	(0.00959)
Vocational	0.00457	0.00480	0.00313	0.00601
Baccalaureate Degree	(0.00491)	(0.00707)	(0.00690)	(0.00801)
Vocational	0.00391	-0.000184	-0.00705	-0.0104
Non-Baccalaureate Degree	(0.00466)	(0.00341)	(0.00939)	(0.00894)
N	4836606	4836606	4742912	4742912
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the Base Centrale Scolarité dataset, which contains information on high school students in France. The table shows results for students enrolled in their first year of high school of the tracks (*Seconde*) as well as students in vocational tracks for the fields of study. The dependent variables are equal to one if the student is enrolled in a certain track or field in high school. Controls include age and socio-economic background. Results are clustered at the county level. The treatment geographical unit is a close county next to the actual treatment unit in the same *région* (see 1). Controls include age, honors at the high school graduation exam, and father's socio-economic category. Results are clustered at the county level.

Table A38 – ATT - Educational Choice in Higher Education - Geographical Placebo

	Women		Men	
Close Counties				
Math-Intensive	0.00220	0.0256	-0.0227	-0.0166
	(0.0175)	(0.0176)	(0.0216)	(0.0584)
Unbiased Science	0.0275*	0.00188	-0.000750	0.0000584
	(0.0144)	(0.0248)	(0.00862)	(0.0236)
N	75795	74430	41787	40999
Close Counties 2				
Math-Intensive	0.00608	0.0118	0.0875***	0.0321
	(0.00829)	(0.0197)	(0.0296)	(0.0355)
Unbiased Science	0.00107	0.0158	-0.0222	0.000488
	(0.0318)	(0.0223)	(0.0316)	(0.0169)
N	81017	79578	44591	43778
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the OVE data set 2010, 2013, and 2016 and the historic waves restricted to students between 17 and 35 years old, who graduated in metropolitan France and are enrolled in initial training. The dependent variable is the likelihood of entering a certain track. Controls include age and parents' socio-economic category. Results are clustered at the county level, and weighted using the OVE's administrator weights. The first half of the table defines the treatment geographical unit as a close county next to the actual treatment unit in the same *région* (see 1), and the second half a close county but in a different *région*. Controls include age, honors at the high school graduation exam, and father's socio-economic category. Results are clustered at the county level.

Table A39 – ATT - Educational Choice in High School - Timing Placebo

	Women		Men	
Fields				
Computer Science	0.00000406	0.00000905	0.0000934	0.000111
	(0.00000760)	(0.0000117)	(0.0000666)	(0.0000824)
Math-Intensive	-0.00738	-0.00663	0.0142	0.0140
	(0.00586)	(0.00576)	(0.00950)	(0.00881)
Unbiased Science	-0.00234	-0.00135	0.00557	0.00594
	(0.00531)	(0.00566)	(0.00426)	(0.00447)
N	1359170	1359170	1758665	1758665
Tracks				
Academic	0.0129**	0.00919***	0.00503***	0.00775***
	(0.00632)	(0.00345)	(0.00183)	(0.00182)
Vocational	-0.0157*	-0.0103*	-0.00980*	-0.00998*
Baccalaureate Degree	(0.00802)	(0.00548)	(0.00519)	(0.00536)
Vocational	-0.0175***	-0.0118	-0.0168*	-0.0138
Non-Baccalaureate Degree	(0.00578)	(0.00742)	(0.00988)	(0.0110)
N	4621386	4621386	4524997	4524997
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the BCS dataset, which contains information on high school students in France. The table shows results for students enrolled in their first year of high school of the tracks as well as students in vocational tracks for the fields of study. The dependent variables are equal to one if the student is enrolled in a certain track or field in high school. Controls include age and socio-economic background. Results are clustered at the county level. The timing used to defined treatment is 3 years prior to the actual treatment. Results are clustered at the county level.

Table A40 – ATT - Educational Choice in Higher Education - Timing Placebo

	Women		Men	
Year 3				
Math-Intensive	-0.00945	-0.0111	0.0330	-0.0486
	(0.0169)	(0.0200)	(0.0224)	(0.0794)
Unbiased Science	0.00530	0.00582	-0.00920	-0.0141
	(0.00433)	(0.0111)	(0.0149)	(0.0226)
N	81017	79601	44591	43829
Year 4				
Math-Intensive	0.00862	0.0118	-0.0300	-0.0409
	(0.0112)	(0.0101)	(0.0248)	(0.0291)
Unbiased Science	-0.0101	0.00101	-0.0135	-0.0126
	(0.00762)	(0.0171)	(0.0121)	(0.0261)
N	81017	79601	44591	43829
Controls	No	Yes	No	Yes

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. I use the OVE data set 2010, 2013, and 2016 and the historic waves restricted to students between 17 and 35 years old, who graduated in metropolitan France and are enrolled in initial training. The dependent variable is the likelihood of entering a certain track. Controls include age and parents' socio-economic category. Results are clustered at the county level, and weighted using the OVE's administrator weights. Year 3 and Year 4 refer to the timing used to defined treatment : 3 years prior to the actual treatment or 4 years prior to the treatment.

B.6 Mechanisms

Table A41 – ATT - Share of Students Passing the Graduation Exam (in % of Enrolled)

	Women			Men			Total		
	Academic	Techno	Vocational	Academic	Techno	Vocational	Academic	Techno	Vocational
Sit for the exam									
ATT	11.92	7.901	110.7*	29.03	-9.628	120.7	40.95	-1.727	231.4
	(55.92)	(68.56)	(64.21)	(28.18)	(44.16)	(87.82)	(56.12)	(107.8)	(150.0)
ATT									
with controls	9.985	122.8**	46.31	0.276	66.12	-11.89	10.26	189.0	34.42
	(43.65)	(57.33)	(42.77)	(25.05)	(64.79)	(82.34)	(46.67)	(121.9)	(123.0)
N	1598	1598	1598	1598	1598	1598	1598	1598	1598
Pass the Exam									
ATT	0.208	0.401	2.529	1.270	-1.281	-0.841	0.676*	-0.450	0.109
	(0.333)	(0.706)	(2.356)	(0.889)	(1.240)	(0.768)	(0.403)	(0.387)	(0.937)
ATT									
with controls	0.000637	-0.509	1.214	0.660	-2.224*	-2.077***	0.293	-1.349	-1.104
	(0.361)	(1.397)	(2.901)	(1.368)	(1.283)	(0.694)	(0.731)	(0.971)	(1.249)
N	1598	1598	1598	1598	1598	1598	1598	1598	1598

Notes : Standard errors in parenthesis. This table reports the average treatment effect on the treated (ATT) as measured by Callaway and Sant'Anna (2021) using *csdid*. The dependent variables are the number of students who sit for the exam and the percentage of students successfully graduating from high school, using data from the DEPP, from 2000 to 2016. Controls are unemployment in the county, and the average year of broadband access in the county (calculated from Malgouyres et al. (2021) from the city-level data).