Non-Cognitive Skills and Labor Market Expectations: Survey and Experimental Evidence from French Vocational Students

Lewin NOLDEN*
Under the supervision of Prof. Pierre Cahuc
and Prof. Clément de Chaisemartin

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Abstract

In 2022 and 2023, the French employment agency intervened in vocational schools to address students' low employment rates when entering the labor market. This study analyzes the spillover effects of this intervention on students' expectations and non-cognitive skills. Expectations and non-cognitive skills are elicited from vocational students currently enrolled in their final year who have not yet received the intervention themselves. The results show moderate changes in students' expectations and significant increases in non-cognitive skills, with scores on four out of five personality traits and locus of control rising by around 5% of a standard deviation per intervention year. The survey further reveals that non-cognitive skills strongly predict students' expectations and partly explain the gender expectations gap. This is crucial to better target students in the future and for understanding differential outcomes for male and female vocational students in the labor market. The study also addresses the challenges posed by overall and differential attrition and discusses the impact of the limited number of individual-level control variables. These considerations are essential to contextualize the unexpectedly large effect estimates and to understand the broader implications of the intervention.

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1 Introduction

An important determinant of the success of an educational system is the share of students successfully entering the labor market after graduation. In France, this measure has been problematically low for vocational school students, the next generation of electricians, builders and other vocational workers. Of the cohort graduating from vocational schools in 2021, depending on the diploma, only between 28% and 40% were employed six months after leaving their school (DEPP 2024b). Recent research has shown that one potential channel through which policy makers can impact this shortcoming in the French context is through facilitating links between employers and students during their education (Cahuc and Hervelin 2020). In order to do so, the French employment agency France Travail is intervening in a large number of vocational schools since 2022. The direct effects of this intervention on the labor market outcomes of students treated in previous years are currently analyzed by the scientific team that set up the experiment (more information here Cahuc et al. 2020). This paper concerns itself with a different channel through which the intervention may influence students outcomes: students labor market expectations and non-cognitive skills.

I analyze a survey eliciting information about labor market expectations and non-cognitive skills from students currently enrolled in their final year at French vocational schools participating in the intervention performed by the French employment agency. Non-cognitive skills are elicited in the survey using two concepts. Firstly, the big five personality traits that measure among other things how outgoing, organized or emotionally stable students are. Secondly, Locus of Control, a measure of how students perceive their control over life outcomes. The intervention itself targets practical skills, like writing a good CV, but also personal skills, like identifying one's strengths and presenting oneself to potential employers. The students answering the survey have not yet received the intervention themselves, but were exposed to their seniors and teachers who took part in the intervention for up to two years.
I leverage the random assignment of schools to treatment to investigate whether being at a school where the employment agency intervened in previous years changes current students labor market expectations and non-cognitive skills. I identify intention to treat effect estimates, regressing multiple outcomes from the survey on treatment assignment, controlling for students gender, degree, and local economic conditions in my main specification. To account for confoundedness of treatment take up, I identify the local average treatment effect, running a two stage least squares model instrumenting treatment execution with treatment assignment.

My analysis suggests, that the intervention at schools does have significant spillover effects on currently enrolled students' expectations and non-cognitive skills. The intervention seems to increase students subjective six month job-find probability (around 1% increase), their perceived preparedness for job-search (up to 5% of a standard deviation per treatment year) as well as their expected probability of enjoying their first job (up to 2%). Furthermore, I find suggestive evidence that students at treated schools are shifting their plans towards entering the labor market rather than continuing their studies and reduce their expectations to receive a permanent contract. More strikingly, the intervention seems to increase students non-cognitive skills almost across the board. For 4 of the 5 personality traits as well as for Locus of Control, students at treated schools exhibit strong increases (especially when at schools treated since 2022). Effect sizes are large, with significant coefficients consistently reaching 5% of a standard deviation increase per year of treatment assignment. Effects on both expectations and non-cognitive skills are heterogeneous with respect to gender, with men emerging as the drivers behind most, but not all of the documented effects.

How important expectations and non-cognitive skills are for labor market outcomes has been consistently documented in the recent economics literature. For example, having overly optimistic expectations has been shown to impact the job-search behavior of unemployed workers, increasing the length of their unemployment spells (Spinnewijn 2015; A. Mueller and Spinnewijn 2023). An overly optimistic vocational student might underestimate the difficulty of finding a job when trying to enter the labor market. They might reject otherwise competitive wages, thinking they would receive better offers from competitors, or they might just not send as many applications as they should to maximize their chances. Labor market expectations may therefore play a key role in explaining vocational students' low labor market insertion rates. Non-cognitive skills on the other hand have been shown to be increasingly important on the labor market across disciplines (Deming 2017) and have also been modeled to explain job-search behavior (Caliendo et al. 2015; Flinn et al. 2024). If vocational students are lacking some of these important skills, this again might contribute to their poorer performance on the labor market. Given these findings in the literature, the success or failure of an intervention aimed at facilitating students labor market entry might depend on the extent to which it is capable of improving non-cognitive skills and moderating overoptimistic expectations.

Furthermore, little is known about how expectations and non-cognitive skills interact. The survey performed at vocational schools allows me to create a link between non-cognitive skills and elicited expectations. This descriptive analysis shows, that differences in non-cognitive skills explain significant parts of the variation in expectations. In particular, the subjective 6-month job-find probability, perceived preparedness for job-search and the expected probability of liking the first job, are strongly correlated with non-cognitive skills. The survey furthermore allows to disentangle expectations by gender and explain differences in expectations by differences in non-cognitive skills. The size of the gender gap in expectations that can be explained by non-cognitive skills varies, but explains for example up to 23% of the difference in perceived preparedness for job-search in the sample. Better understanding how these gender specific expectations are related to non-cognitive skills is integral to better understand men and women's differential outcomes. For example, the analysis of the gender "aspirations" gap discussed in the literature (see for example Azmat et al. 2023a) could greatly profit from further investigation of the link between expectations and non-cognitive skills.

While I can not yet observe the outcomes of the students participating in the survey, I could compare students expectations today with realizations of previous cohorts. This, to a limited extent, allows me to investigate expectation bias. For example, I document that on average, men have more overly optimistic employment expectations than women, meaning that their expectations are further away from observed employment rates in previous years than women's. I document a similar but less clear picture for salary expectations. In the context of vocational students labor market outcomes, this might motivate targeting men's expectations in future interventions.

The main limitation of my findings relates to the limited amount of individual student level information and issues connected to potential differential attrition. I address the first problem by providing a wide range of robustness checks, including changes to the sample, inclusion of variables at different aggregations, and inclusion of different controls. My results are robust to those checks, but only the inclusion of further controls in the future will be able to entirely eradicate this concern. I address the second issue with an in depth analysis of differential attrition across years of randomization. I find that differential attrition is a limited concern for schools randomized in 2022, but a serious one for schools randomized in 2023. To illustrate how differential attrition might impact my results, I present analysis

of Lee bounds (Lee 2009) that show that under extreme selection assumptions, the previously found effects might be invalidated. I provide arguments for why I think the extreme assumptions are unlikely to occur in practice, but highlight that it is important to keep in mind how sensitive the results are to them.

I hope that this paper can serve as the basis for further analysis of the experiment in the coming months and years. The students who responded to the survey will repeat the survey once they themselves took part in the intervention by France Travail. Comparing their answers before and after the intervention, taking into account the spillover effects I document here, will yield interesting insights. Furthermore, once information about the actual labor market outcomes of students answering the survey is available in the coming years, it will be worthwhile to connect their expectations and non-cognitive skills to their actual employment paths.

Section 2 reviews the related literature, followed by an introduction to the experimental setup in Section 3. The survey methodology is detailed in Section 4, with descriptive survey evidence presented in Section 5. For readers primarily interested in the empirical analysis of the intervention effects, the results are comprehensively discussed in Section 6. The implications and limitations of these findings are discussed in Section 7, and the study concludes with final remarks in Section 8.

2 Literature

2.1 Non-Cognitive Skills

Non-cognitive and social skills have been shown to be increasingly important determinants of success on the labor market (Deming 2017). Among non-cognitive skills, personality traits and locus of control have been given special attention. Early examples for the study of personality traits in economics include Bowles et al. 2001, Heckman et al. 2006 and Almlund et al. 2011. Locus of Control has been studied among others by Caliendo et al. 2015 and Caliendo et al. 2022. In this paper, whenever non-cognitive skills are mentioned, they refer to personality traits and locus of control. In the literature, the term is used to describe a variety of measures including and sometimes going beyond the measures used here.

The concept of personality in Psychology has been present for decades, with the field of Personality Psychology emerging in the 1970s. From this field, the widely shared taxonomy of the "Big Five" personality traits emerged. It is used in a wide array of disciplines reaching far beyond psychology, into sociology, anthropology and economics (Almlund et al. 2011). Table 1 presents the five personality traits and their definitions: Extraversion, Agreeableness, Conscientiousness, Open-Mindedness and Emotional Stability.

The Big Five have been shown to have significant predictive power with regards to educational and labor market outcomes. Higher values of Open-Mindedness and Conscientiousness have been linked to increased years of schooling (Almlund et al. 2011). Conscientiousness and Agreeableness have emerged as predictors of earnings (see Risse et al. 2018 for a review). Agreeableness for example has been shown to explain parts of the earnings differential between men and women, on the one hand due to the higher endowments of Agreeableness that women display (Braakmann 2009; Nyhus and Pons 2012), and on the other hand due to different impacts of holding this trait for men and women (G. Mueller

and Plug 2006). In the recent literature, attempts have been made to incorporate personality traits into labor search models (Flinn et al. 2024), with the model recovering Agreeableness and Emotional Stability as primary drivers of gender wage gaps, acting through the traits' impacts on bargaining power. Conscientiousness and Emotional Stability have been linked to shorter unemployment spells, acting through their impact on job-search intensity (Uysal and Pohlmeier 2011). Finally, the Big Five seem to be quite stable throughout an individuals life, but do change during adolescence (Elkins et al. 2017), with especially conscientiousness being relatively fluid (Prevoo and Ter Weel 2015).

Table 1: The Big Five Personality Traits

Trait	Definition of Trait
Extraversion	An orientation of one's interests and energies toward the outer world of people and things rather than the inner world of subjective experience; characterized by positive affect and sociability.
Agreeableness	The tendency to act in a cooperative, unselfish manner.
Conscientiousness	The tendency to be organized, responsible, and hardworking.
Open-Mindedness	The tendency to be open to new aesthetic, cultural, or intellectual experiences.
Emotional Stability	Predictability and consistency in emotional reactions, with absence of rapid mood changes.

NOTE: definitions from the American Psychological Association Dictionary, VandenBos 2007, cited in Almlund et al. 2011. The trait Open-Mindedness is also referred to as Openness to Experience. The trait Emotional Stability is the inverse of the trait Neuroticism that is mentioned frequently in the literature.

The other non-cognitive skill that got a lot of attention in the literature is Locus of Control. Locus of control captures how much control an individual perceives to have over their lives (VandenBos 2007). People with an external Locus of Control don't perceive themselves as in charge of their lives' outcomes. People with an internal Locus of Control on the other hand perceive the future as under their control and dependent on their actions. Higher values of internal Locus of Control have been shown to be positively correlated with higher earnings and educational attainment (Baron and Cobb-Clark 2010, Piatek and Pinger 2016) and increased job-search intensity, while higher values of external Locus of Control have been associated with lower reservation wages (Caliendo et al. 2015; McGEE 2015). Among other factors, increased job-search intensity might drive positive outcomes for people with higher internal Locus of Control.

That adolescents non-cognitive skills can be influenced by interventions has been found in many experimental settings over the years (for a review of the psychology literature on school based socio-emotional skill interventions see Cipriano et al. 2023). Within the economics literature, a recent example shows how interventions targeting non-cognitive skills can improve students outcomes (Sorrenti et al. 2024) and another recent study shows that interventions targeting career development can spill over into the non-cognitive domain (Carlana et al. 2022). Outside controlled experimental contexts, Azmat et al. 2023b show that students non-cognitive skills adapt to large macro shocks.

2.2 The Role of Expectations for Labor Market Outcomes

A large literature in economics has concerned itself with the role of expectations for decision making. In the context of education, students' expectations about financial payoffs and non-pecuniary factors have been shown to explain decision making, for example choice of major. Prominent examples include Wiswall and Zafar 2015 and Bleemer and Zafar 2018 (for a great review see Giustinelli 2022). Students' expectations with regards to labor market outcomes have furthermore been found to vary by gender with men exhibiting higher earnings expectations than women (Mazza and Hartog 2011; Schweri et al. 2009). It has furthermore been documented that students tend to overestimate returns to education (Botelho and Pinto 2004) with high achieving students, female students, and more senior students having more realistic expectations (Hastings et al. 2016). While most of the studies mentioned before study college students, the findings seem to be generalizable also to community college students in the US, a system closer to vocational education (Baker et al. 2018). To the best of my knowledge, expectations of vocational school students have not been analyzed in the literature as such.

The reason why students' expectations are relevant for their labor market outcomes beyond their degree choices relates to the way overoptimistic expectations can impact job-finding. Overoptimism has been shown to reduce job-search intensity, increasing the length of the unemployment spell (Spinnewijn 2015; A. Mueller et al. 2021). In particular, unemployed workers seem to expect a much higher job-offer arrival rate than is seen in reality, impacting their search behavior (Conlon et al. 2018). Some active labor market interventions have succeeded at reducing this overoptimism, correcting workers expectations (Arni 2016). Given the cited findings, correcting students expectations should be of primary concern to a policy maker interested in helping students achieve better outcomes.

3 Experimental Setup

This section introduces the randomized control trial (RCT), known under the name AvenirPro, funded by the French ministries of Education and Labor and executed by the French employment agency France Travail (formerly Pôle Emploi). The main objective of the experiment is to evaluate the impact of an intervention by a case worker from France Travail at French vocational schools (Lycées Professionnels) on students labor market insertion rates after graduation. The goal of this paper is to analyze potential spillover effects of the intervention in 2022 and 2023 on current final year students' expectations and non-cognitive skills. The detailed information about the experiment comes from the intermediate report written by the scientific team analysing the experiment (see Cahuc et al. 2023).

3.1 The French Vocational School System

When finishing lower secondary education after 9 years of studies, students in France have the choice between multiple tracks of upper secondary education. Figure 1 gives an overview of the different available tracks. Relevant for the context of this paper, is the vocational track that students can choose. The vocational track can lead to two different diplomas. Students can either choose to join a two year program, leading to a diploma called "certificat d'aptitude professionelle" (CAP). Or they can choose to join a three year program leading to a "baccalauréat professionelle" (BacPro). Around 11% of all students choose the CAP track, while 22% of all students choose the BacPro track (Testas et al. 2018). Overall, the BacPro track is more flexible. Students enrolled in it have the option to change into the technological and general tracks to obtain a baccalauréat technologique or baccalauréat

général, diplomas that are generally associated with better labor market outcomes. BacPro students furthermore have the right to join a university program directly after obtaining their diploma. CAP students on the other hand do not have the option to easily change into the general and technological tracks. They can however, after finishing their diploma, join the second year of the BacPro track to gain a baccalauréat professionel.
Employment rates after graduation for both diplomas are below the national average, with CAP students performing even worse than BacPro students. Of the cohort graduating with a BacPro in 2021, 40% were employed by January 2022, while only 28% of those with a CAP diploma were at the same time (DEPP 2024b).

Motivated by these numbers, the intervention performed by the French employment agency targets the final year students in the CAP and BacPro programs to facilitate their integration into the labor market. The red boxes in Figure 1 mark the moment of intervention.

3.2 Experimental Setup

The intervention of AvenirPro consists of two phases. The first one takes place during the school year, the second takes place after the students graduate and leave their school.
During the first phase of the intervention, every agency of France Travail participating in the experiment delegates one employee to spend 90% of their working hours performing the intervention at four schools. The case worker performs the intervention as part of the already existing class modules dedicated at improving students knowledge about the labor market ("module d'insertion professionnelle" for BacPro students and "Accompagnement personnalisés, AP" for CAP students). Every intervention session is supposed to take place with the case worker of France Travail and a member of the pedagogic staff, i.e. a teacher, one of the main reasons why the intervention might have spilled over on the current cohort.
The exact content of the intervention can vary across different case workers and student profiles, depending for example on the specific degree prepared or the number of students present during the intervention. However, all intervention sessions include elements targeting the following topics: improving professional knowledge, learning about the labor market, learning about job-search, mastering digital tools, preparing job interviews, working on CVs and motivation letters and building a professional project.
During the second phase, those students that decided not to continue their studies or to continue their studies but doing an alternance (part time work next to studies), had the chance to keep in contact with the case worker of France Travail that intervened at their school previously. The contact could take the form of phone calls, emails, SMS, or in person meetings at the agency.

Topics Covered during the Intervention

- **Knowledge about the Labor Market:** Providing information about open positions, their location, possible career perspectives, and teaching about the notion of tight and open labor markets. Present information about the available public services, like financial or logistic aid.
- **Identifying and Valuing one's Skills:** Teaching students about what is expected from them on the labor market and how they can distinguish themselves from other applicants. Targeting students learning about their own capabilities, focusing on social and inter-personal skills, self image and professional behavior.

Figure 1: Flowchart of Educational Tracks in the French School System

Note: This flowchart illustrates the different educational routes after lower secondary school. The left side presents the general track and technological tracks, the right side the vocational track. Solid arrows signify a students standard progression through the educational system. The dashed line show changing options that vocational track students have during their studies (the options for general and technology track students are omitted from this graph). The boxes marked red, signify the year and track were the France Travail intervention takes place.

- **Job-Finding Strategies and Techniques:** Developing students job-search capabilities by helping them to formulate their strategy taking into account their individual goals. Teaching skills necessary for successful applications, like writing CVs and cover letters.
- **Job Interviews:** Improving students' self confidence during a formal interview situation, utilising mock interviews.

- **Meeting Employers:** Facilitating students access to the labor market by inviting local employers to the intervention session.

Overall, in 2022, treated students were exposed to 9 hours of intervention on average. The standard deviation of treatment hours received was 4.3 hours. The maximum hours of intervention students were exposed to is 39 hours, the minimum 2 hours. For the 2023 intervention, this information has not yet been evaluated, however if anything, is expected to be slightly higher.

3.3 Randomization

After a pilot program in 2021, a first group of schools was randomized in 2022 and a second in 2023. All schools that were assigned to treatment in 2022 retained their treatment assignment in 2023 if they still wished to continue. On the following pages I will often refer to the 2022 and 2023 samples, meaning the sample of students at schools randomized in 2022 and 2023 respectively. The randomization was performed in the following steps:

1. France Travail provides a list with suitable agencies that are capable to perform the intervention.
2. Using the location of the agencies and vocational schools, travel distances by car from agency to school are estimated. Only schools within a 30 minutes (urban areas) and 60 minutes (rural areas) car ride from a suitable agency are further considered.
3. Schools in an agencies' perimeter are then ranked according to their average 6-month labor market insertion rate (based on data from the inserjeune database, see DEPP 2024b) and grouped in pairs such that schools with the most similar insertion rate are put together. In the case that there are more than four pairs in an agencies' perimeter, the four with the lowest insertion rate are kept.
4. Finally, within each pair, one school is assigned to receive the treatment and the other is assigned to the control group.

The effective randomization following this procedure was hindered by some territorial and organizational restrictions. Some regional directorates of France Travail required that treated schools are in the same Département as the agency, even if the proximity rule above assigned a close by school outside the Département. In some rural areas, it was not possible to assign control schools as the number of similar schools was too low. Futher, some schools in Ile de France that participated in a previous intervention (Objectif Premier Emploi), performed by a private firm called ADECCO, could not be considered in the randomization. In addition, for the two regions that participated in the pilot in 2021, Grand-Est and Pays de Loire, the randomization from the pilot were reused in 2022. Schools that took part in the pilot (6 in Grand-Est and 5 in Pays de Loire) were offered to continue with the treatment (10 decided to do so) and were hence strictly speaking not randomized. The remaining schools in the two regions were grouped in strata of 4 with two of them randomly assigned to treatment.

Table 2: Overview of Treatment Assignment by Year

School Randomization	Number	Treated in 2022	Control in 2022	Treated in 2023	Control in 2023
Assigned to Treatment 2022	185	147	38	124	61
Assigned to Control 2022	205	9	196	14	191
Sum 2022	390	156	234	138	252
Assigned to Treatment 2023	164			118	46
Assigned to Control 2022	158			22	136
Sum 2023	322			140	182
Sum	712	156	234	278	434
Treated at least once	296				
Treated exactly once	167				
Treated exactly twice	129				

2024 Cohort Students at Randomized Schools	Number	Treated in 2022	Control in 2022	Treated in 2023	Control in 2023
Assigned to Treatment 2022	23,901	20,001	3,900	16,729	7,172
Assigned to Control 2022	25,188	1,558	23,630	1,945	23,243
Sum 2022	49,089	21,559	27,530	18,674	30,415
Assigned to Treatment 2023	20,537			15,541	4,996
Assigned to Control 2023	19,995			2,659	17,336
Sum 2023	40,532			18,200	22,332
Sum	89,621	21,559	27,530	36,874	52,747
Treated at least once	39,759				
Treated exactly once	22,074				
Treated exactly twice	17,685				

NOTE: This table gives an overview of the schools participating in the experiment by year of randomization. It also gives the number of students in 2024 at schools that were randomized in 2022 and 2023.

Effectively, 712 schools can be considered as having been properly randomized. 390 of them in 2022 and 322 in 2023. Table 2 reports details of treatment assignment by year. Further it provides insights into the confoundedness of treatment execution.

The confoundedness of treatment execution can be traced back to multiple problems manifesting themselves between the randomization and execution. Firstly, after the schools were randomized according to the four steps outlined above, the list was transferred to France Travail's local agencies in order to be validated. Some schools that were initially assigned to treatment were changed to control for divers reasons, among them human ressource constraints, change in management, presence of an already existing interventions, etc., leading to the first dimension of imperfect take up. Secondly,

once the list was finalised, the schools were contacted by France Travail and offered to participate in the experiment. Some schools that were offered the treatment did not eventually accept it, some of them citing resource constraints, lack of interests, disagreement with the interventions goal, others did simply not respond initially or stopped responding after agreeing to participate at first. Table 2 shows that the degree of imperfect take up is quite large. Only around 80% of schools assigned to treatment in 2022 were effectively treated in 2022, and only 67% of them continued to be treated in 2023. Among schools assigned to treatment in 2023, only 72% eventually received the treatment.

Within schools assigned to treatment, some classes were randomly assigned to receive the treatment. As outlined above, for the analysis of this study, only the school level randomization is being considered as I investigate the spillover effects on all students at treated schools, hence no details on the class level randomization will be provided.

3.4 School and Student Level Data

In order to compare the balance of treatment assignment, student and school characteristics are required. Multiple data sources are used to enable this comparison over a large set of variables.

Student level data for the 2023/2024 cohort: The French education ministry provided a list with information about all students currently enrolled in their final year at schools participating in the experiment. For all those students information about gender and degree is available. The degree variable is defined at the most granular level available (mefstat 11) and aggregated in 10 groups for most of the following analysis. This data allows to calculate shares of students enrolled in specific degress across treated and untreated schools for the 2023/2024 cohort. It furthermore allows to calculate gender shares for the 2023/2024 cohort.

Student level data for the 2022/2023 cohort: For the 2022/2023 cohort (that did not respond to the survey), student level data is available as part of the data base Base Centrale Scolarité (DEPP 2023) provided by the French education ministry. This data base includes information about students gender, age, nationality and socio-economic background. The information is aggregated at the school level to calculate shares that can then be used to compare treated and control schools.

School employment data: For all academic years from 2019 to 2022, data on school performance is available as part of the Inserjeune data base provided by the French education ministry (DEPP 2024a). For every school the 6, 12, and 18 month labor market insertion rate of their students is reported in absolute terms (i.e. not specified by degree). It is furthermore reported how many students continue their studies and decide not to enter the labor market. Another measure reported is so called school value added, where the actual labor market insertion rate is compared to what would be expected given the local market (i.e. if value added is positive, the school outperformed other schools in the region).

National employment data by degree: As part of the same data base (DEPP 2024b) the degree level employment rates after 6 and 12 months are reported at the national level for students finishing their studies in the 2020/2021 cohort.

National wage data by degree, gender and age: The French Labor Force Survey (INSEE 2022)

includes representative information about wages in 2024. Filtering for individuals between 15 and 25 years, degree and gender allows to estimate wages corresponding to the students participating in the experiment.

Local labor market information: The data base Filosofi (INSEE 2023) is used to merge data on local labor market conditions for the year 2020. Labor market information is aggregated at the "Zone Emploi 2020" level, which is the respective school's commuting zone. The data base includes local unemployment, local living standard, inequality measures, and poverty rates.

All these data points are used to compare schools and their cohorts across years in the following balancing checks.

3.5 Representativeness and Balance

Table A1 compares schools taking part in the experiment, either as control or treated schools, with other vocational schools. Using school level data on employment insertion for previous cohorts, performance indicators from the Inserjeune data base (DEPP 2024b) and other student characteristics from the Base Central Scolarité (DEPP 2023) for the 2022/2023 cohort, it documents that participating schools fared consistently worse than non participating schools in previous years. Participating schools had lower labor market insertion rates, lower value added, are located in economically weaker areas, display lower shares of French students in the 2022/2023 cohort and higher shares of students from working class backgrounds. Overall, these findings echo the selection process by which schools were included into the experiment since when more than four pairs could be build around one France Travail agency, only the worst performing ones were included. It hence seems reasonable to assume that this selection mechanism is the main driver for the observed differences.

Table A2 and Table A3 report school level balancing tests of treatment assignment for 2022 and 2023 respectively. Table A4 reports results of regressions of treatment assignment on the individual level characteristics available for the 2023-2024 cohort, namely sex and degree. At the school level, the 2022 randomization has produced perfectly balanced results. The 2023 randomization displays imbalances, with a lower share of students in the electrotechnics and energy related disciplines for the 2023/2024 cohort, a higher share of students with parents holding executive employee (cadre) status (2022/2023 cohort), and a higher share of students having pursued their studies after graduation for the academic years 2019/2020 and 2020/2021. The individual level balancing test for both years is almost perfectly balanced, with only the electrotechnics and energy related disciplines predicting treatment status significantly for the 2023 sample.
To summarize, while the sample of schools participating in the experiment tends to include more poorly performing schools than the average, the random assignment of schools to treatment for the years 2022 and 2023 seems to have been largely successful, given the data available here. The following section will introduce the survey performed among schools participating in the experiment.

4 Survey

In late 2023, all schools taking part in the experiment were invited to participate in a survey on expectations and non-cognitive skills. The surveys' goal is to connect information about non-cognitive skills as defined in the introduction, with final year students labor market expectations. It was performed on a digital device in class under supervision of a teacher. The current section will outline the information elicited in this survey and will analyse both students and schools response behavior.

4.1 Elicitation of Expectations

The survey elicits information on vocational school students expectations. Broadly speaking, three categories of expectations questions can be differentiated. The first one concerns students' plans to enter the labor market and how long they think it would take them to find a job. The second elicits information about students subjective preparedness for job search. The third includes expectations about job properties, like pay and contract type.
In the whole survey Likert scales are used for categorical questions. They take the format disagree strongly, disagree a little, neutral, agree a little, agree strongly. Probabilities are elicited using scales that can be freely moved across all integers between 0 and 100.

Study Plans and Employment Expectations: The first question of the survey asks whether students want to continue their studies after graduating or whether they want to enter the labor market straight away. The employment expectations are elicited at the 6-month and 12-month horizon. Besides their individual employment expectations, the survey further elicits the 6-month job finding probability students assign to their peers in previous years.

Students Subjective Preparedness for Job-Search: Students subjective preparedness for job search is elicited based on five questions. The questions asked whether a student thinks they know how to find job offers that fit their profile, whether they feel well prepared for job interviews, whether they think they will have to be mobile in order to find a fitting job, whether they can count on family and contacts when applying and finally, whether they are already in contact with employers. To consolidate the answers to these five questions into one measure of subjective preparedness for job-search, one latent factor is extracted using principal component factor analysis.

Expected Job-Properties: The expected job properties include a question about the net earnings a student expects in their first job as well as questions about the contract type they expect to hold. Contract types can be permanent, temporary or self-employment. Finally, students are asked to report the probability that they will like the job they find and whether they find it interesting.

4.2 Elicitation of Non-Cognitive Characteristics

The Big Five Personality Traits: The Big Five personality traits are elicited making use of the short form of the Big Five Inventory-2, the BFI-2-S, developed by Soto and John 2017. The questionaire consists of 30 questions that, again answered on a Likert scale as described above. The Likert scale is numbered from 1 to 5, 1 for disagree strongly, 5 for agree strongly. Some of the questions are reverse coded so as to avoid a systematic impact of positive question phrasing. The 30 questions map into 15 so-called facet scales. The 15 facet scales in turn map into 5 so-called domain scales, the Big Five: extraversion, agreeableness, conscientiousness, negative emotionality, and open-mindedness. Following

Cubel et al. 2016, the Big Five domain scales are computed simply by averaging the positively coded 6 base questions mapping into them. For all Big Five domain scales, higher values hence indicate higher endowments.

Locus of Control: Information on Locus of Control is elicited using 8 questions answered on the same Likert scale as before. Following the literature on Locus of Control (Caliendo et al. 2022, Piatek and Pinger 2016, Cobb-Clark et al. 2014) a measure of the same is constructed in two steps. In a first step, factor analysis is utilised to identify components of Locus of Control that can be interpreted as internal and external Locus of Control. The items loading onto external Locus of Control are then reverse coded so that all items increase in internal Locus of Control. In a second step, the factor analysis is repeated using the reverse coded items. This isolates one factor that is increasing in internal Locus of Control. Using the loading weights of this factor, the final measure is constructed. An alternative measure merely taking the average of the 8 questions (reverse coded for those identified as loading of external locus of control) is constructed to test the main measures robustness. Figure B5 reports details of this process.

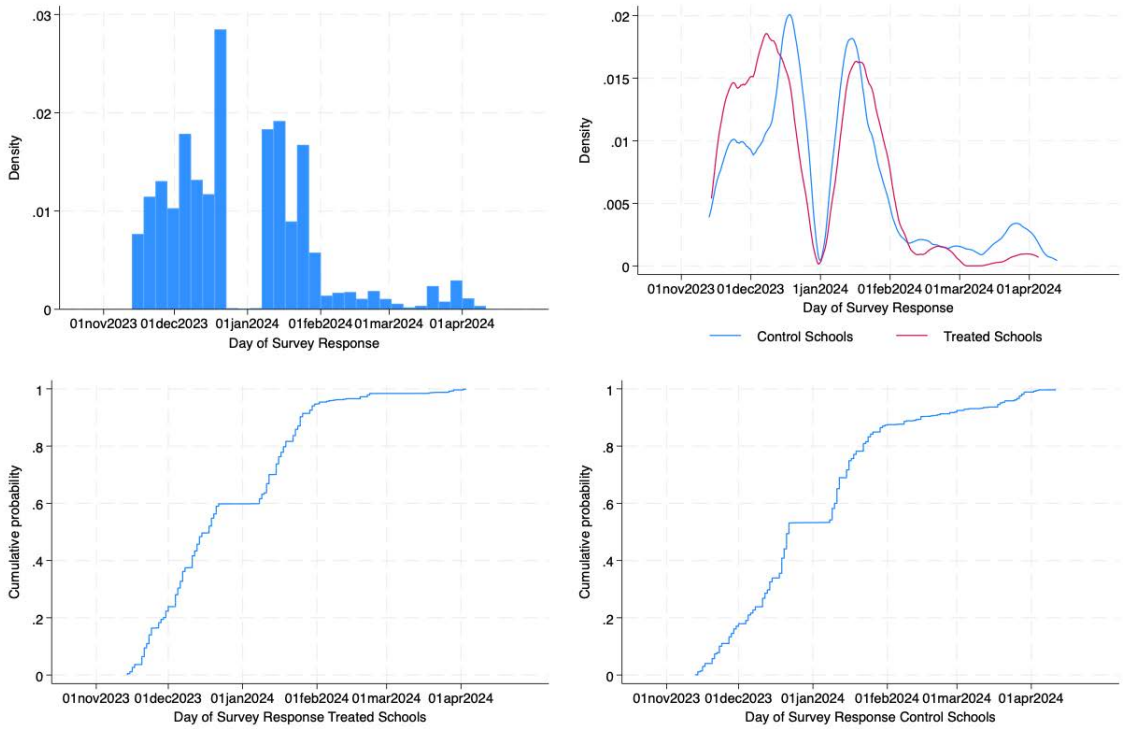


Figure 2: Survey Response by Date

4.3 Quality of Response and Attrition

Response Quality

The survey was open from mid November 2023 until the end of December and was then reopened in January 2024 to collect more response. The last survey response was collected on 11 April 2024. Figure 2 shows that both among treated and control schools, the bulk of responses was collected in the first months of the survey. 80% of responses among both groups were in by mid January, however, more treated schools responded in the first month followed by a catch up of control schools. While this would not concern many students, it is not impossible that some students already received the first intervention session by late January when responding to the survey.

Overall, students responding to the survey seem to have taken it seriously. Appendix Figure B1 reports the distribution of time taken to respond to the survey by treatment status. A Kolmogorov-Smirnov test fails to reject the equality between the the treatment and control groups, indicating that treatment status does not increase time spent on the survey. The mean response time is around 10 minutes, the median around 8 minutes and 30 seconds.
Another indication for the overall rationality of response is that at least on average, students seem to have understood the questions on employment probabilities, assigning higher values to their subjective 12-month job-find probability than to the 6-month job-find probability. Appendix Figure B3 shows that the cumulative distribution of the 12-month job-find probabilities stochastically dominates the 6-month job find probability. Further Appendix Figure B2 documents a high correlation of 0.71 between the responses elicited for the two time horizons, indicating internal consistency.
Most students further seem to have rational salary expectations, details are reported in Appendix Figure B4. Only 1.56% of the sample report expected net monthly earnings above 5000 euros. For all these students, wages are winsorized to 5000 euros so as to avoid irrational wage expectations to skew the estimates below.

Attrition

Among all schools taking part in the RCT, 343 responded to the survey, representing 48.2% of schools. Within responding schools, 43.8% of students answered the survey (averaged across treated and control and across randomization years). Overall, survey responses from 18,835 students could be collected, representing 21,0% of students at all schools taking part in the RCT. Table 3 gives an overview of which students got treated in which year as well as how confounded the treatment execution is in this sub-sample. While among responding schools who were randomized in 2022, a larger share was assigned to the control group, the opposite is true for schools randomized in 2023. At the end, slightly more of the individual responses are from students at treated schools.

Table 3 furthermore gives insight into differential attrition by randomization year. When looking at the responses received vs the expected overall responses (i.e. the number of students at all schools that are part of the RCT), for both randomization years, students at treated schools have higher response rates. While this difference is moderate in the 2022 sample (2.8 percentage points), it is large in 2023 (6.7 percentage points). The difference in attrition of students within schools that have submitted at least one response is much lower for 2022 with an absolute difference of only 0.2 percentage points. In 2023, this difference again is large, with 12.3 percentage points difference. Differential attrition hence seems to be a bigger issue for the 2023 randomization year, a problem that will make identification for

the 2023 sample difficult.

Appendix Table B1 presents a regression of school response on school characteristics. For the 2022 sample, none of the characteristics about degree shares and school performance predict response. The main factor that explains school response seems to be the effective execution of treatment. While treatment assignment has no significant effect on school response in either year, having received the treatment twice does predict school response in the 2022 sample. Furthermore, quite a few of the student and performance characteristics do predict response for the 2023 sample, while for the 2022 sample no serious predictors emerge.

Appendix Table B2 performs the same exercise with student characteristics of students at responding schools. Students response in the 2022 sample does not seem to be impacted by the schools treatment status. Some of the individual level variables for the 2022 sample do predict student response within responding schools. One of them is sex, but also two of the degree groups emerge as significant predictors. For the 2023 sample, treatment assignment does predict student response. Also treatment execution and some of the degrees emerge as predicting within school response in 2023. This echoes the higher imbalance in individual response as well as the differential attrition in absolute terms that was documented before.
When running the same regressions for all students at all schools, no matter whether the school responded or not, we get a similar result which is documented in Appendix Table B3. However, it needs to be interpreted with caution, as students at schools who did not submit a single survey response did not attrite in the same sense as non responding students at responding schools. However again, and most importantly, treatment assignment does not predict student response in 2022, but does in 2023.

A final analysis with regards to differential attrition is reported in Appendix Table B4. It reports regressions of student response on student characteristics interacted with treatment assignment and results of an F-test testing whether the interaction coefficients are jointly zero. This hypothesis can not be reject for within school and overall response in 2022, but can be rejected at the 10% significance level for within school response in 2023. The results of the F-test support the claim that differential attrition is a limited issue for the 2022 sample and a more serious one for the 2023 sample.

Since attrition can be a major problem when trying to identify treatment effects in randomized control trials, the discussion about the potential negative effects of attrition, especially for the 2023 sample, will be continued in section 6.

Table 3: Overview of Treatment Assignment by Year (among schools answering the survey)

Responding Schools	Number	% all schools	% within responding	Treated in 2022	Control in 2022	Treated in 2023	Control in 2023
Assigned to Treatment 2022	98	53.0%		88	10	80	18
Assigned to Control 2022	104	50.7%		7	99	7	97
Sum 2022	202	51.8%		93	109	87	115
Assigned to Treatment 2023	75	45.7%				57	18
Assigned to Control 2023	66	41.8%				9	57
Sum 2023	141	43.8%				66	75
Sum	343	48.2%		93	109	153	190
Treated at least once	159						
Treated exactly once	77						
Treated exactly twice	82						

Responding Students	Number	% all schools	% within responding	Treated in 2022	Control in 2022	Treated in 2023	Control in 2023
Assigned to Treatment 2022	5,630	23.6%	43.5%	5,158	472	4,755	875
Assigned to Control 2022	5,229	20.8%	43.7%	363	4,866	521	4,708
Sum 2022	10,859	22.1%	43.6%	5,521	5,338	5,276	5,583
Assigned to Treatment 2023	4,715	23.0%	49.8%			3,670	1,045
Assigned to Control 2023	3,261	16.3%	37.5%			409	2,852
Sum 2023	7,976	19.7%	43.9%			4,079	3,897
Sum	18,835	21.0%	43.8%	5521	5,338	9,355	9,480
Treated at least once	9,600						
Treated exactly once	4,646						
Treated exactly twice	4,954						

NOTE: This table gives an overview of the schools participating in the experiment that answered the survey by year of randomization.

5 Descriptive Survey Evidence

The following section reports descriptive evidence from the survey. All results are reported for students who attend schools that were not assigned to treatment. Overall this is the case for 8,490 of the 18,835 students responding to the survey.

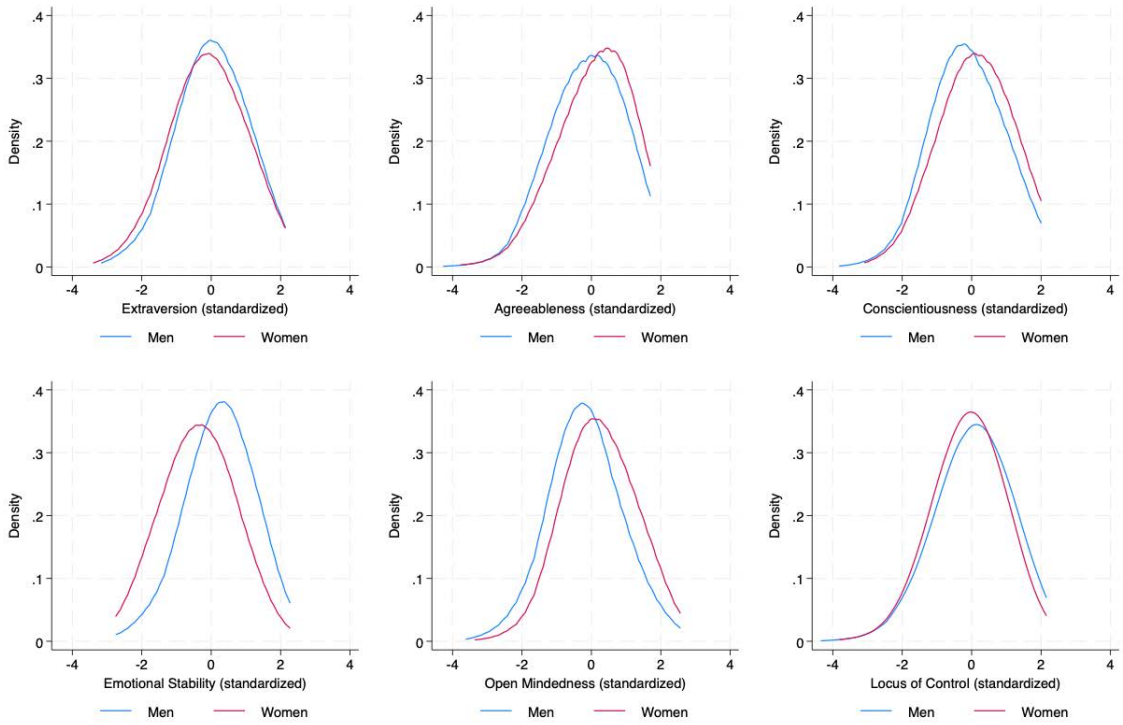
5.1 Summary Statistics

Table 4: Summary Statistics of Control School Students

	(1) All		(2) Men		(3) Women		(4) Men - Women	
	Mean	SD	Mean	SD	Mean	SD	Difference	p-value
Personality Traits and Locus of Control								
Extraversion	3.45	0.72	3.49	0.70	3.40	0.75	0.09	(0.000)
Agreeableness	3.86	0.67	3.80	0.66	3.95	0.67	-0.15	(0.000)
Conscientiousness	3.62	0.69	3.55	0.67	3.72	0.69	-0.16	(0.000)
Open Mindedness	3.34	0.65	3.23	0.63	3.50	0.63	-0.27	(0.000)
Emotional Stability	3.19	0.80	3.40	0.73	2.90	0.79	0.50	(0.000)
Locus of Control	3.77	0.57	3.80	0.59	3.71	0.55	0.09	(0.000)
Locus of Control, alternative	3.65	0.56	3.71	0.57	3.57	0.53	0.13	(0.000)
Labour Market Entry Plans								
Pursue Studies	3.86	1.35	3.71	1.39	4.07	1.26	-0.36	(0.000)
Pursue Studies Yes	0.71	0.46	0.66	0.47	0.76	0.42	-0.10	(0.000)
Employment Probability Expectations								
Subjective 6-Month Job-Find Probability	0.61	0.25	0.65	0.25	0.56	0.24	0.09	(0.000)
Subjective 12-Month Job-Find Probability	0.72	0.26	0.75	0.25	0.68	0.26	0.07	(0.000)
Subjective 6-Month Cohort Job-Find Probability	0.51	0.20	0.53	0.20	0.48	0.19	0.05	(0.000)
Irrational Job-Find Probality (6-Month ¿ 12-Month Probability)	0.15	0.36	0.14	0.35	0.17	0.37	-0.03	(0.002)
Expected Job Properties								
Expected Probability of Liking Job	0.61	0.25	0.63	0.25	0.59	0.24	0.04	(0.000)
Expect Permanent Contract	0.54	0.50	0.56	0.50	0.52	0.50	0.04	(0.001)
Expect Temporary Contract	0.36	0.48	0.34	0.47	0.40	0.49	-0.06	(0.000)
Expect to be Entrepreur	0.09	0.29	0.10	0.30	0.08	0.28	0.02	(0.001)
Perceived Preparedness for Job-Search								
Preparedness for Job-Search (factor weight)	3.64	0.73	3.68	0.74	3.58	0.72	0.10	(0.000)
Preparedness for Job-Search	3.67	0.71	3.71	0.72	3.63	0.70	0.08	(0.000)
I know how to find a suitable job offers	3.45	1.03	3.49	1.04	3.39	1.03	0.10	(0.000)
I feel ready for job interviews	3.66	1.15	3.74	1.12	3.54	1.18	0.20	(0.000)
To find a job, you need to be mobile and flexible	3.85	1.08	3.82	1.10	3.89	1.05	-0.07	(0.003)
When looking for a job I can count on my family/contacts	3.93	1.16	3.90	1.16	3.96	1.17	-0.05	(0.035)
I am already in contact with potential employers	3.48	1.34	3.58	1.31	3.35	1.38	0.23	(0.000)
Observations	8490		4997		3493		8490	

Table 4 reports summary statistics for all non-cognitive skill dimensions and expectations variables elicited from the survey. As has been previously documented women display higher values of conscientiousness, open mindedness and agreeableness and lower values of emotional stability. Surprisingly though, different to a variety of previous studies (Nyhus and Pons 2012; G. Mueller and Plug 2006; Flinn et al. 2024) in the sample of students considered here, men display higher values of Extraversion than women. It is not immediately clear why this would be the case, apart from the possibility that specific types of male and female students select into vocational education. All differences are statistically significant, with the largest difference being that for emotional stability, where the mean for men lies about 63% of a standard deviation above the mean for women, and the smallest difference for extraversion, with the mean for men about 12% of a standard deviation above the mean for women. For both versions of the measure of Locus of Control, men display higher values than women with about 25% of a standard deviation difference. Figure 3 gives graphical insight into this relationship showing that the differences are observable along most of the distribution.

Figure 3: Distribution of Big Five and Locus of Control by Gender



With regards to the expectations variables, Table 4 documents that, not controlling for field of study, men seem to have on average significantly higher expectations, almost across the board. Men expect quicker employment, are surer they are going to like the job they end up with, expect to find permanent contracts rather than temporary contracts more often and feel more prepared for job search. The

biggest difference towards the other direction emerges for students plans to continue their studies after graduating, with more women reporting to be planning on doing so. This seems broadly similar to what has previously been document in the literature, as discussed in Section 2.2, with men consistently reporting more optimistic expectations.

5.2 Non-Cognitive Skills and Expectations

5.2.1 Regressing Expectations on Non-Cognitive Skills

Expectations and non-cognitive skill endowments differ significantly across gender in the sample. It remains unclear howwever, how the two are connected. Table 5 reports regressions of expectations on non-cognitive skills. All regressions control for gender, degree, local economic conditions, and school fixed effects. Also reported are the squared semi-partial correlation coefficients of each regressor, representing the proportion of variance in the outcome variable that is explained by the regressor alone. The variable "Continue Studies Yes" is a binarized version of the continue study or enter labor market question on the survey, coded with yes for people who agree strongly or a little and no for undecided and those who disagree. The other four expectations variables, log expected salary, subjective 6-month job-find probability, preparedness for job-search and probability of liking job were chosen to represent a broad range of expectations indicators.

Most importantly, Table 5 shows that non-cognitive skills and expectations are strongly correlated. This is not surprising given the literature discussed in section 2.1 that documents strong links between non-cognitive skills and labor market outcomes. However, it is interesting that this link transcends to expectations in this sample. The share of the variance in the outcome variables explained by non-cognitive skills varies. Including non-cognitive skills increases the r-square by 0.0053 for log expected salary. It increases the r-square by 0.1580 in the regression on perceived preparedness for job-search. For the latter, the increase can be considered as large, showing how informative non-cognitive skills can be about expectations.
Among non-cognitive skills, Extraversion and Locus of Control emerge as having the highest relative explanatory power. While Locus of Control is correlated with better labor market outcomes in reality, this is less clear for Extraversion. This is relevant in so far, as higher levels of Extraversion might increase optimism without improving outcomes on the labor market. Conscientiousness is positively correlated with all variables that it significantly predicts. Emotional Stability further is positively correlated with optimism across the expectations variables but explains only a small share of variance in the outcomes compared to the other skills. Open Mindedness, the one non-cognitive skill most closely related to cognitive skills (Almlund et al. 2011), is strongly associated with an increase in the likelihood of a student wanting to continue their studies. Agreeableness is the only non-cognitive skill that is significantly negatively correlated with some of the expectations measures. In particular, increased levels of Agreeableness are correlated with reduced earnings expectations and a reduction in the perceived likelihood of finding a job six months after graduating. In the literature Agreeableness emerged as the one personality trait that is negatively correlated with real earnings, something apparently echoed in the expectations measure here.

Documenting these strong correlations highlights that the intervention might impact students expectations through its impact on non-cognitive skills. To disentangle the relationship between non-cognitive skills and optimism or overoptimism however, data on students outcomes on the labor market would be required which is not available for now.

Table 5: Expectations and Non-Cognitive Abilities

	(1) Continue Studies Yes	(2) Log Expected Salary	(3) Subj. 6-Month Job-Find Prob.	(4) Prepared for Job-Search (standardized)	(5) Prob. of Liking Job
Extraversion (standardized)	0.028***	0.032***	0.040***	0.134***	0.021***
	(0.006)	(0.010)	(0.003)	(0.010)	(0.003)
	[0.002]	[0.001]	[0.017]	[0.022]	[0.005]
Agreeableness (standardized)	0.024***	-0.040***	-0.012***	0.003	0.007**
	(0.005)	(0.011)	(0.003)	(0.010)	(0.003)
	[0.002]	[0.002]	[0.002]	[0.000]	[0.001]
Conscientiousness (standardized)	-0.007	0.027***	0.020***	0.071***	0.035***
	(0.007)	(0.010)	(0.003)	(0.009)	(0.004)
	[0.000]	[0.001]	[0.003]	[0.005]	[0.011]
Emotional Stability (standardized)	0.003	0.017*	0.015***	0.014	0.014***
	(0.006)	(0.010)	(0.004)	(0.011)	(0.004)
	[0.000]	[0.000]	[0.002]	[0.000]	[0.002]
Open Mindedness (standardized)	0.035***	0.007	-0.001	0.019**	-0.002
	(0.005)	(0.010)	(0.003)	(0.008)	(0.003)
	[0.005]	[0.000]	[0.000]	[0.001]	[0.000]
Locus of Control (standardized)	0.015**	-0.003	0.021***	0.156***	0.022***
	(0.006)	(0.012)	(0.003)	(0.010)	(0.003)
	[0.001]	[0.000]	[0.005]	[0.032]	[0.006]
Observations	8490	8462	8490	8490	8490
R^2 increase from Non-Cog	.0182	.0053	.0735	.158	.0822
Gender Controls	X	X	X	X	X
School Controls	X	X	X	X	X
Degree Controls	X	X	X	X	X
Economic Controls	X	X	X	X	X

Note: This table reports results of OLS regressions of expectations variables on Big Five personality traits, Locus of Control as well as gender, school, educational and economic controls. Standard errors are reported in parantheses. Squared Semi-Partial Correlation Coefficients are reported in square brackets (the squared semi-partial correlation coefficient of each regressor represents the proportion of variance in the outcome variable that is explained by the regressor alone). "R^2 increase from Non-Cog" gives the increase in R^2 from including all personality traits and Locus of Control compared to a model without them and just the controls.

5.2.2 Decomposing the Gender Expectations Gap

Given that non-cognitive skills seem to have considerable predictive power over expectations in the sample, this section looks at how differences in non-cognitive skills across gender explain differences in expectations. It is particularly interesting to investigate whether non-cognitive skills impact expectations differently by gender. For the intervention this is relevant in so far, as it could uncover channels through which expectations can be impacted most efficiently. Table 6 reports results of a Oaxaca decomposition of the expectations gap by gender. I follow the standard pooled decomposition equally performed in G. Mueller and Plug 2006. For each expectations variable, I first estimate a pooled linear model and then one for men and women each.

Pooled:

$$Y_i = X_i'\beta_p + \epsilon_i \tag{1}$$

Men:

$$Y_{im} = X_{im}'\beta_m + \epsilon_{im} \tag{2}$$

Women:

$$Y_{if} = X_{if}'\beta_f + \epsilon_{if} \tag{3}$$

Where i represents the individual, m represents males and f females. X_{im}' and X_{fm}' are male and female characteristics respectively and X_i' are the pooled characteristics, including the non-cognitive skills, as well as school and degree fixed-effects and local economic indicators. ϵ represents the respective error terms. The difference in expectations between men and women is then expressed in terms of averages:

$$\bar{Y}_m - \bar{Y}_f = \bar{X}_m'\beta_m - \bar{X}_f'\beta_f \tag{4}$$

With β_m and β_f from equations (2) and (3), and then decomposed such that:

$$\bar{Y}_m - \bar{Y}_f = \underbrace{\left[\bar{X}_m - \bar{X}_f\right]'\beta_p}_{explained} + \underbrace{\left[\bar{X}_m'(\beta_m - \beta_p) - \bar{X}_f'(\beta_f - \beta_p)\right]}_{unexplained} \tag{5}$$

With β_p being the coefficient from the pooled regression in equation (1). The first term of equation (5) hence captures the difference in expectations that is "explained" by differences in endowments of the variables in X. The second term captures the gap that stems from differences in the coefficients between men and women and is hence considered as being "unexplained".
Table 6 reports the results of this decomposition. In the bottom part of the table, the overall part of the gap that is explained by the non-cognitive skills is presented in absolute and relative terms. Unsurprisingly, the higher the correlation between non-cognitive skills and an expectation variable, the higher the share of the gap explained by differences in endowments. In that logic, the smallest part of the gap is explained by non-cognitive skills for the earnings expectations gap, and the highest part for the perceived preparedness for job-search. The panel labeled "explained" shows more detailed information about which non-cognitive skill explains what part of the difference. While for all expectations variables, the unexplained gap is bigger than the explained gap, non-cognitive skills do not contribute to it a lot. The only significant coefficient in the panel labeled "unexplained" is that for Open Mindedness in the decomposition of the subjective 6-month job-find probability. The negative coefficient

indicates that women increase their job-find expectations more with increased Open Mindedness than men, closing the gap in job-find expectation. Other aspects documented in the literature, for example that men and women display different coefficients on the impact of Agreeableness on realized earnings (G. Mueller and Plug 2006), does not seem to translate into differential correlation between this trait and salary expectations. Overall, it does therefore not seem as if differential impact of non-cognitive skills on expectations is a major driver.

For the intervention this could imply that targeting specific non-cognitive skills would only have limited differential effects on men and women with regards to their expectations. However, depending on which expectations measure a policy maker wants to impact, they might want to target the population that is less endowed with the non-cognitive skill correlated with it to close the expecations gap.

Table 6: Oaxaca Decomposition of Expectations by Sexe

	(1) Continue Studies Yes	(2) Expected Salary	(3) Subj. 6-Month Job-Find Prob.	(4) Prepared for Job-Search	(5) Prob. of Liking Job
overall					
Men	0.664***	1633.8***	0.648***	3.683***	0.630***
	(99.37)	(151.58)	(181.62)	(353.88)	(180.12)
Women	0.765***	1339.3***	0.561***	3.581***	0.592***
	(106.61)	(128.99)	(138.84)	(293.51)	(145.55)
difference	-0.101***	294.5***	0.0870***	0.102***	0.0381***
	(-10.30)	(19.68)	(16.13)	(6.38)	(7.10)
explained	-0.0464***	91.73***	0.0232***	0.00667	0.0304***
	(-4.60)	(5.64)	(4.14)	(0.41)	(5.42)
unexplained	-0.0546***	202.8***	0.0638***	0.0957***	0.00763
	(-4.11)	(9.27)	(8.78)	(4.73)	(1.06)
explained					
Extraversion (standardized)	0.00337***	5.184***	0.00482***	0.0162***	0.00257***
	(3.61)	(3.68)	(5.01)	(5.11)	(4.25)
Agreeableness (standardized)	-0.00530***	10.64***	0.00265***	-0.000609	-0.00153**
	(-3.93)	(4.77)	(3.73)	(-0.31)	(-2.21)
Conscientiousness (standardized)	0.00166	-4.967**	-0.00470***	-0.0169***	-0.00835***
	(1.08)	(-2.15)	(-5.02)	(-6.01)	(-7.42)
Emotional Stability (standardized)	0.00202	16.17***	0.00963***	0.00896	0.00846***
	(0.53)	(2.85)	(4.58)	(1.50)	(4.06)
Open Mindedness (standardized)	-0.0145***	-2.484	0.000523	-0.00776**	0.00101
	(-6.21)	(-0.75)	(0.44)	(-2.32)	(0.86)
Locus of Control (standardized)	0.00230**	-1.103	0.00326***	0.0243***	0.00348***
	(2.42)	(-0.72)	(4.92)	(6.62)	(5.14)
unexplained					
Extraversion (standardized)	0.0000577	-0.551	-0.0000224	-0.000274	-0.0000290
	(0.22)	(-1.08)	(-0.18)	(-0.73)	(-0.22)
Agreeableness (standardized)	0.0000711	-0.515	-0.0000922	-0.000913	-0.0000545
	(0.14)	(-0.58)	(-0.34)	(-1.17)	(-0.20)
Conscientiousness (standardized)	0.000622	0.431	0.000281	0.00147	0.000480
	(1.06)	(0.47)	(0.83)	(1.57)	(1.36)
Emotional Stability (standardized)	0.000618	-0.404	-0.000169	0.00137	-0.000191
	(0.44)	(-0.19)	(-0.21)	(0.60)	(-0.25)
Open Mindedness (standardized)	0.00107	-0.563	-0.00136**	-0.00245	-0.000244
	(1.11)	(-0.39)	(-2.45)	(-1.60)	(-0.47)
Locus of Control (standardized)	0.000250	0.877	-0.0000811	-0.000636	-0.0000673
	(0.61)	(1.17)	(-0.36)	(-0.91)	(-0.30)
Constant	-0.221	-1081.0	0.636	-0.478	-0.350
	(-0.22)	(-0.75)	(1.11)	(-0.35)	(-0.63)
Observations	8490	8490	8490	8490	8490
Part Explained by Non-Cog	**-.01**	**23.44**	**.02**	**.02**	**.01**
Share Explained by Non-Cog	**10.36%**	**7.96%**	**18.59%**	**23.65%**	**14.84%**
Degree Controls	X	X	X	X	X
School Controls	X	X	X	X	X
Economic Controls	X	X	X	X	X

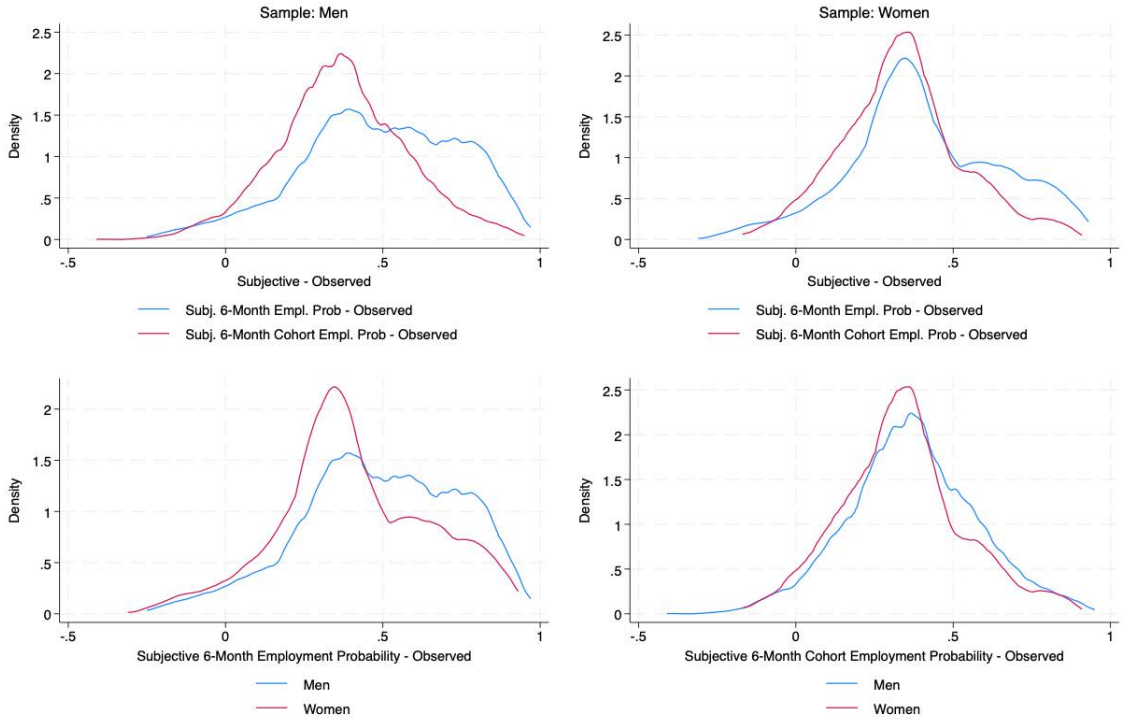
t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 Expectations and Reality

As outlined before, what really makes expectations interesting in the context of vocational students' labor market outcomes is how they relate to reality. Overly optimistic students might underestimate the difficulties they face when entering the labor market, leading to worse outcomes than if they had come prepared. Since actual outcome data on the students participating in the survey is not yet available, it is not possible to quantify the extent of overoptimism among students exactly. What is possible, is to compare students' expectations today to previous cohorts realizations. Data to do so is available for two of the expectations variables considered before: 6-month job-find probability and expected net monthly earnings.

Figure 4: Observed vs. Subjective Employment Probabilty Bias by Sex

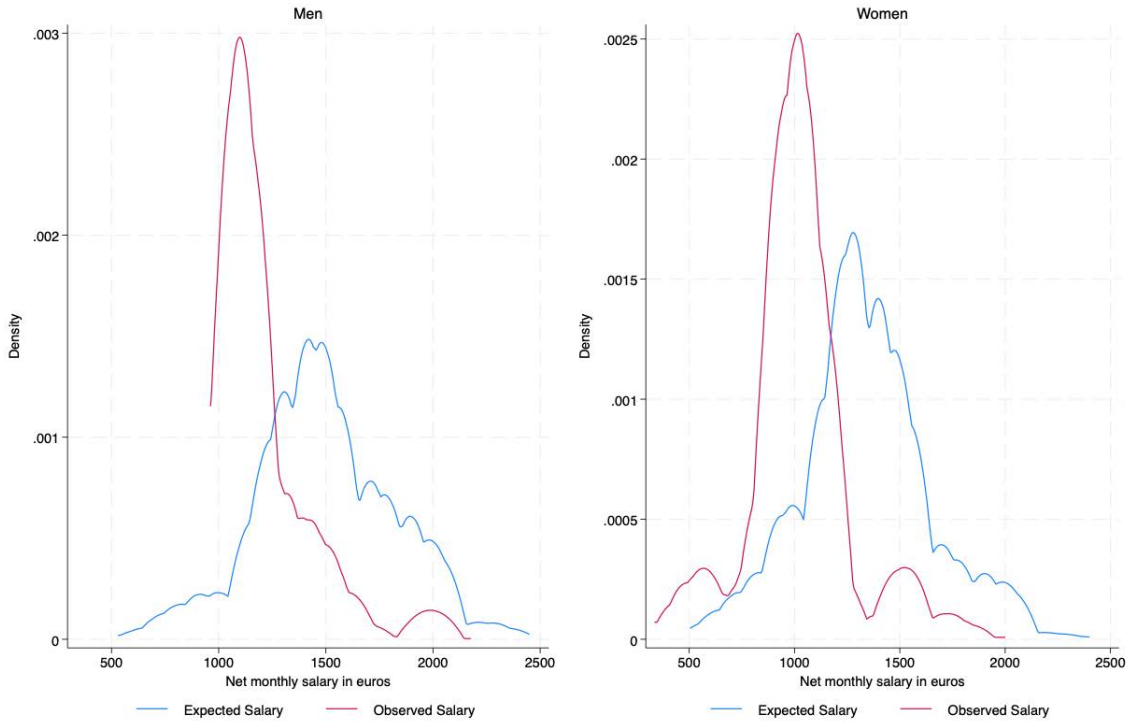


Note: For the degrees of 5078 of the 8490 students in the control group, data on the 2020/2021 cohort's observed employment insertion rate after six months is available (DEPP 2024b). This graph plots the difference between this observed employment insertion rate and the subjective Job-Find Probability for the individual and the cohort. Graphs are differentiated by sex.

Figure 4 gives insights into multiple aspects of potential overoptimism. All graphs plot the difference between the expected 6-month employment probability, either for oneself or for the previous cohort, and the observed 6-month employment probability for people with a specific degree at the national level (DEPP 2024b). On the four panels of Figure 4, higher values hence signify higher expectations relative to what is observed for a degree at the national level. The first two graphs in the upper row show that both men and women exhibit employment expectations well beyond what is observed for

previous cohorts. Furthermore it shows that women expect for themselves employment probabilities closer to what they expect for previous cohorts whereas men more consistently expect better chances for themselves. The second row shows that men on average exhibit higher positive bias then women, both when comparing the respective expectations for themselves and for the cohort. It needs to be stressed that the conclusion drawn from this analysis are indicative at best. Since employment data by degree is only available at the national level and only for previous cohorts, it remains to be seen how realistic students' expectations were when they enter the labor market themselves.

Figure 5: Expected vs. Observed Net Monthly Salary by Sex

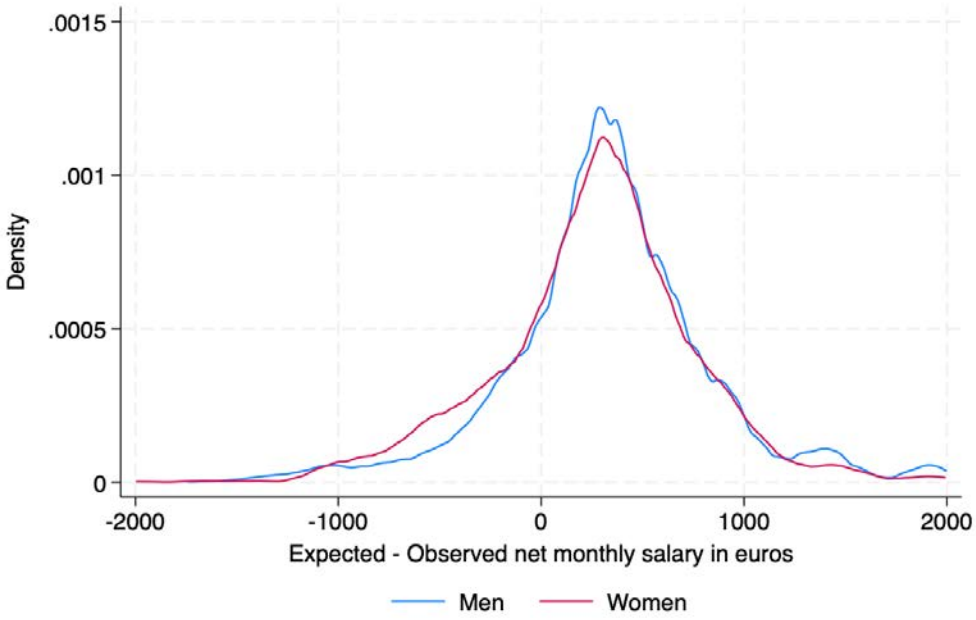


Note: Note: For the degrees of 6521 of the 8490 students in the control group, data on observed wages are available. Observed wages are computed from the 2021 French Labor Force Survey (INSEE 2022) for workers between 15 and 25 years old. Wages are computed at the level of the degree a student prepares.

Figure 5 shows a similar trend for expected and observed wages. Wages are taken from the French labor force survey for people between 15 and 25, averaged by degrees nationally. Because it is aggregated in that way, the measure of wages is presumably noisy, but should be good enough to inform about the underlying trend. The distribution of both male and female wage expectations sits to the right of the distribution of wages that students in previous cohorts could expect for their specific degrees. The mode of both observed and expected wages for men lies to the right of the mode for women, indicating that men both earn and expect more, at least aggregated over the occupations they select into. Figure 6 however shows, that for the most part, men and women are equally biased with the

mode of the difference between expected and observed net monthly income being at around 300 Euros of net monthly earnings for both of them. While this is the case, women seem to be more present in the left tail of the distribution of differences, indicating that they are more often expecting wages below the real observed wages for their degree.

Figure 6: Absolute Difference of Expected and Observed Net Monthly Salary by Sex



Note: For the degrees of 6521 of the 8490 students in the control group, data on observed wages are available. Observed wages are computed from the 2021 French Labor Force Survey for workers between 15 and 15 years old. Wages are computed at the level of the degree a student prepares.

Only once the students that participated in the survey this year enter the labor market next year, will it be possible to draw detailed conclusions on biased employment and wage expectations. Connecting the correlational findings between non-cognitive skills and expectations to the realized observations will further this analysis in the next years.

6 Experimental Evidence

In this section I analyze whether the intervention at schools in 2022 and 2023 had spillover effects on the non-cognitive skills and expectations of students today. I consistently refer to the 2022 and 2023 samples, meaning the sample of students responding to the survey in 2024 that are at a school that was randomized in 2022 or 2023 respectively.

6.1 Empirical Strategy

6.1.1 Empirical Models

As discussed before, compliance with the treatment assignment among schools responding to the survey was not perfect. Non-compliance was two-sided, see again Table 3. Of all schools assigned to treatment in the 2022 sample, 10.2% ended up in control in 2022 and 18.4% ended up in control in 2023. Of those assigned to the control in the 2022 sample, 4.8% ended up treated in 2022 and 6.7% ended up treated in 2023. Of the schools assigned to treatment in the 2023 sample, 24% ended up in the control, and of those assigned to the control in 2023, 13.6% ended up treated. To account for this two-sided-non-compliance, I follow Imbens and Rubin 2015 and report results both for the Intention to Treat Effect as well as for the Local Average Treatment Effect.

Intention to Treat Effect (ITT):
To estimate the ITT model, the following equation is specified:

$$Y_{is} = \alpha + \beta^{OLS} T_s + X'_{is}\delta + \epsilon_{is} \tag{6}$$

where Y_{is} represents the outcome of individual i at school s. T_s is an indicator of a school s' random assignment to the treatment. β^{OLS} is the main parameter of interest capturing the intention to treat effect stemming from random assignment to the intervention. The vector X_{is} contains controls. In the main specification this includes gender, diploma type, currently prepared degree, and local economic controls but can vary across specifications. α is a constant. ϵ_{is} is the error term of the model.

Local Average Treatment Effect (LATE):
To account for the two-sided-non-compliance, treatment assignment is used as an instrument for effective treatment execution in order to estimate the intervention's local average treatment effect. The following model is estimated using two-stage least squares:

$$Y_{is} = \alpha + \beta^{IV} D_s + X'_{is}\delta + \epsilon_{is} \tag{7}$$

$$D_{is} = \gamma + \tau T_s + X'_{is}\rho + \eta_{is} \tag{8}$$

where Y_{is} denotes the outcome of individual i at school s. T_s is an indicator of treatment assignment at school s, and D_s is an indicator of treatment execution at school s. β^{IV} is the main parameter of interest capturing the local average treatment effect. The vector X_{is} contains the same controls as in the ITT estimation. α and γ are constants. ϵ_{is} and η_{is} represent the error terms of the respective stages.

6.1.2 Standard Errors

Regarding the question where to cluster standard errors, I follow the recommendations for paired and small strata RCTs with large clusters made in De Chaisemartin and Ramirez-Cuellar 2024 and cluster

them at the strata level instead of the unit level. The experiment at hand falls under the conditions outlined by them, as most strata are consisting of only two schools with only one unit assigned to treatment.

6.1.3 Dealing with Attrition

A major question for the analysis of treatment effects in the context of this study relates to the question of how to deal with strata in which one of the units outcomes are missing, i.e. all strata where only one of the schools responded to the survey. Of the 202 schools randomized in 2022 that responded to the survey, only 66 are part of complete strata. At those 66 schools, responses of 3793 students (out of 10859 overall) were collected. Of the 141 schools randomized in 2023 that responded to the survey, 62 are part of complete strata, with 3653 responding students (out of 7976 overall). For both years, more than half of the responses are hence coming from schools whose counterpart in the strata is not observed.

The question whether strata with attriting units should be dropped in the regression analysis has been debated in the literature in recent years. For example King et al. 2007 and Bruhn and McKenzie 2009 argue for dropping pairs where one unit attritted, the idea being that the remaining complete pairs would allow for an unbiased estimator, with the only downside being the reduced external validity of the estimate. Similarly, Fukumoto 2022 makes the point that if attrition is correlated with the outcome variable, researchers might be better advised to drop the whole pair if one unit in the pair attrits. However, he notes that while it might be better to drop incomplete pairs, the resulting estimator might be biased. Ferman and Ponczek 2017 add, that dropping incomplete pairs comes with a risk, as it is possible that a pair is complete even though its characteristics are associated with attrition in the population, leading to distortions. They further make the important point, that the exact selection rule for which pairs are kept and which are not should be specified in a pre-analysis plan as different selections can lead to differing results (that this has not been done for this study is considered to be a limitation).

Most recently, Bai et al. 2024 analyse the different estimators stemming from dropping and not dropping incomplete pairs on the basis of previous work done by them on matched pair designs (see Bai 2022 and Bai et al. 2022). Just like De Chaisemartin and Ramirez-Cuellar 2024, they show that including pair fixed effects and dropping incomplete pairs are mechanically equivalent. Both papers recommend to practitioners that are interested in recovering the average treatment effect not to include pair fixed effects and hence advise not to drop incomplete pairs. However Bai et al. 2024 also note some identifying assumptions that need to be made in order to recover effects under these circumstances. When not dropping incomplete pairs:

Assumption 1: the estimator for difference in mean outcomes conditional on not attriting can only be interpreted as the average treatment effect for non attriting units if one is willing to make the assumption that the subgroup of schools attriting under treatment assignment corresponds to the subgroup of schools attriting under control assignment.

Assumption 2: the estimator only becomes the average treatment effect if one is further willing to assume that attrition is independent of potential outcomes.

Assumption 3: the estimator becomes a convex-weighted average of the conditional average treatment effect under the weaker assumption of independence of potential outcomes and attrition conditional on observable characteristics (with a more favorable weight than under strata fixed effects).

Given the outlined discussion, I decided to follow the recent recommendations in the literature and do not drop incomplete pairs (or include strata fixed effects in my regressions). With respect to the identifying assumptions, appendix Table B8 and appendix Table B9 report the balance of attriting schools by treatment assignment for 2022 and 2023 respectively. Both find only one barely significant difference between information for previous cohorts and no statistical difference for the information concerning the cohort responding to the survey. Also, as discussed before, appendix Table B1, Table B2, Table B3 and Table B4 show that treatment assignment does not predict attrition of schools and students for 2022 school students, but does predict attrition for 2023 school students.
In the context of the outlined assumptions, I take this previously discussed evidence and conclude that assumption 1 can be reasonably assumed to hold, especially for students at schools randomized in 2022. I will hence interpret my results as the intention to treat effect for non attriting units (OLS) and the local average treatment effect for non attriting units (IV). Assumption 2 and 3 are tougher to test in practice and will be discussed in section 7.

6.2 Balance among Respondents

Overall, the sample of schools and students responding to the survey is well balanced between those assigned to treatment and those assigned to the control, given the information available. Appendix Table B5 and Table B6 report the balancing tests for responding schools randomized in 2022 and 2023 respectively. For 2022 one imbalance is that schools assigned to treatment tend to be bigger in terms of number of students in the 2022/2023 cohort. Three other slight imbalances relate to the school performance metrics for the 2019/2020 cohort, while more recent performance metrics are balanced.
For schools randomized in 2023 a potentially more problematic imbalance arises. The response rate of students within schools that answered the survey is significantly higher in schools assigned to treatment than in schools assigned to control with an absolute difference of 12.3% as documented before. The only other imbalance is a lower share of students enrolled in electronics and energy related degrees in the 2023/2024 cohort, hence an imbalance that directly impacts the observed sample.
Regarding individual characteristics, appendix Table B7 shows that barely any imbalances are present. No significant imbalances emerge for students enrolled at schools randomized in 2022. With regards to students at schools randomized in 2023, again more problematic imbalances appear with being enrolled in an electronics and energy or administrative service degree predicting treatment assignment.

6.3 Results

6.3.1 Effects on Non-Cognitive Skills

Table 7 and 8 report results of the analysis of treatment effects on non-cognitive skills. For all personality traits as well as for Locus of Control, both tables report intention to treat estimates (columns 1-3) and local average treatment effects (columns 4-6). Column 1 and 4 include no controls. Columns 2 and 5 control for degree (aggregated to 10 groups), diploma (BacPro or CAP) and sex. Columns 3 and 6 add local economic indicators to the previous controls (including median living standard and a measure for inequality build as the ratio between the living standard of the 1st and the 10th decile). For each variable, results for students at schools randomized in 2022 are separately reported from

those of students at schools randomized in 2023. In the appendix (section 9) further robustness checks are reported, using a more dis-aggregate version of the degree variables, controlling for quick response times, as well as utilizing different samples (excluding all schools in Grand-Est and Pays de la Loire who's randomization was performed differently; excluding all strata with an attriting unit).
The treatment assignment variable is coded as 0, 1, 2, so as to capture the fact that schools assigned to treatment in 2022 were assigned to treatment for two years while schools assigned to treatment in 2023 can only have been treated once so far. Besides standard p-values, the tables report randomization inference p-values with 1000 permutations. These test how the coefficient changes when treatment is randomly reassigned within strata to asses whether the observed coefficient size stems from the treatment itself or from a specific realization of the randomization.

With the exception of Open-Mindedness, the treatment assignment seems to have had a surprisingly strong positive impact on non-cognitive skills for students at schools randomized in 2022. While the picture for the effects on students at schools randomized in 2023 is less clear, point estimates consistently point in the same direction and reach similar magnitudes as for the 2022 sample, with some of them being significant and others closely above a p-value of 0.1. Further, as expected, in all cases the point estimate of the intention to treat effect is smaller than that of the local average treatment effect in the instrumental variables specification, since the latter identifies the treatment effect on the treated. Including controls only minimally changes the coefficient size for the 2022 sample, echoing the good balance and successful randomization documented before. For the 2023 sample including controls does change point estimates more significantly, as was expected given the imbalance in student degrees.
Especially for schools randomized in 2022 coefficient sizes are large in magnitude. Given that treatment is coded as 0, 1, 2, depending on how many years a school was assigned to treatment, for the ITT estimates, the coefficient needs to be taken times two, as all schools assigned to treatment in 2022 were assigned to treatment in 2023 as well. Similarly in the IV specification, the coefficient refers to the effect of one year of treatment received and must be taken twice for students at schools who received the treatment twice. The highest point estimates indicate effects of up to around 10% of a standard deviation per treated year. How realistic such strong spillover effects are with respect to the literature will be discussed in section 7.

Robustness

The appendix in section 9 includes tables reporting the results of a variety of robustness checks (Extraversion (C1), Agreeableness (C2), Conscientiousness (C3), Open-Mindedness (C4), Emotional Stability (C5), Locus of Control (C6)).

The first robustness check relates to the way the student degree variable was constructed (panel A1 & A2, column 2 and 5). To analyse the robustness with respect to different aggregations, a disaggregate degree variable with 38 different degree groups is used. For the 2022 sample, the results are robust to this change, with only slight differences in coefficients. Also for the 2023 sample the inclusion changes little and does not render any previously insignificant ITT coefficients significant, nor vice versa, apart from Agreeableness, where the point estimate changes slightly with a p-value close to but above 0.1. More concerning is that point estimates for Extraversion, Agreeableness, Emotional Stability and Locus of Control become negative in the IV specification, however with large p-values. A possible explanation could be that including 38 more regressors overfits the model, leading to large standard errors.

For the next robustness check, the 5% fastest responders are dropped to make sure that irrationally fast completed questionaires do not impact the results. Fast responders where not dropped in the first place to avoid biasing the sample, as fast response and treatment status as well as other unobservables might be correlated. However, Appendix Figure B1 and Appendix Table B13 show that differential response time is not a big issue. The former shows the distribution of response time and gives the result of a Kolmogorov-Smirnov test of equality of distributions which cannot be rejected (p-value 0.297). The latter provides regression estimates of response time on treatment assignment, with a slightly significant value for 2023. For the 2022 sample, results are robust to the exclusion of the top 5% fastest responders. Point estimates barely change and significance is preserved. Similarly for the 2023 sample, magnitudes barely change. Overall this indicates that effects are not driven by people quickly filling out the survey answering overly positively or negatively.

In a next step the robustness of the estimates for 2022 is analyzed by excluding all schools located in Grand-Est and Pays de la Loire (panel B1, columns 1-6). As explained before, in those two regions schools were randomized in strata of four. Of the 10859 responses collected for 2022, 5654 remain when excluding the respective schools. Apart from Agreeableness where the coefficients are almost collectively rendered insignificant and small, the results are robust to this change. For Extraversion, the size of the point estimates decreases and coefficients are only significant at the 5% instead of the 1% level. For Agreeableness, previously significant estimates become insignificant, however with p-values close to 0.1. For the other outcomes little changes. While the balancing tests were not reperformed, the limited change of coefficients across the inclusion of the available controls indicates balance across the available information.

Finally, the results robustness is analysed by excluding non complete pairs from the regression (panels C1 & C2, columns 1-6). As discussed before, this changes the interpretation of the coefficient on treatment assignment, as it no longer recovers the estimator for difference in mean outcomes conditional on not attriting (or the average treatment effect for non attriting units under the assumptions made) but rather a convex-weighted average of the same. I still consider it an interesting exercise in order to better understand the validity of the results described above. Balancing tests for the sample of complete pairs are reported in appendix Tables B10, B11 and B12. As expected, given the pairwise design, balance is given at the school level for both years. At the individual level however, the 2023 sample remains quite unbalanced with multiple individual characteristics emerging as signficiantly predicting treatment.
For the 2022 sample, the results are robust to this sample change. Coefficients remain significant with many of them increasing in magnitude. The results of 2023 also seem robust in the sense that point estimates keep the same sign. However some of the coefficients previously significant at the 10% level become insignificant. Given the imbalances in the 2023 complete pair sample as well as the reduced number of observations, the documented robustness of the previous coefficients to this change is questionable.

Table 7: Non-Cognitive Skills

Part 1: Non-Cognitive Skills

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Extraversion (standardized) 2022						
Treatment Assigned	0.045***	0.045***	0.045***	0.056***	0.055***	0.057***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]			
Observations	10859	10859	10859	10859	10859	10859
Extraversion (standardized) 2023						
Treatment Assigned	0.019	0.020	0.020	0.029	0.030	0.030
	(0.455)	(0.431)	(0.428)	(0.455)	(0.430)	(0.428)
	[0.653]	[0.530]	[0.548]			
Observations	7976	7976	7976	7976	7976	7976
Agreeableness (standardized) 2022						
Treatment Assigned	0.049***	0.046***	0.047***	0.061***	0.057***	0.059***
	(0.002)	(0.000)	(0.000)	(0.002)	(0.001)	(0.000)
	[0.001]	[0.001]	[0.000]			
Observations	10859	10859	10859	10859	10859	10859
Agreeableness (standardized) 2023						
Treatment Assigned	0.065*	0.056*	0.057*	0.099*	0.086*	0.088*
	(0.082)	(0.081)	(0.078)	(0.080)	(0.081)	(0.076)
	[0.217]	[0.374]	[0.402]			
Observations	7976	7976	7976	7976	7976	7976
Conscientiousness (standardized) 2022						
Treatment Assigned	0.060***	0.057***	0.058***	0.074***	0.071***	0.072***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]			
Observations	10859	10859	10859	10859	10859	10859
Conscientiousness (standardized) 2023						
Treatment Assigned	0.052*	0.039	0.042	0.079*	0.060	0.065
	(0.098)	(0.165)	(0.131)	(0.095)	(0.167)	(0.132)
	[0.091]	[0.137]	[0.157]			
Observations	7976	7976	7976	7976	7976	7976
Degree Controls		X	X		X	X
Diploma Controls		X	X		X	X
Gender Controls		X	X		X	X
Economic Controls			X			X
Randomization Reps:	1000					

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Non-Cognitive Skills

Part 2: Non-Cognitive Skills

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Open-Mindedness (standardized) 2022						
Treatment Assigned	0.013	0.015	0.015	0.016	0.018	0.019
	(0.390)	(0.176)	(0.178)	(0.386)	(0.169)	(0.169)
	[0.248]	[0.077]	[0.073]			
Observations	10859	10859	10859	10859	10859	10859
Open-Mindedness (standardized) 2023						
Treatment Assigned	-0.016	-0.026	-0.025	-0.025	-0.039	-0.038
	(0.721)	(0.406)	(0.427)	(0.721)	(0.406)	(0.428)
	[0.824]	[0.605]	[0.585]			
Observations	7976	7976	7976	7976	7976	7976
Emotional Stability (standardized) 2022						
Treatment Assigned	0.048***	0.048***	0.052***	0.059***	0.059***	0.065***
	(0.008)	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)
	[0.007]	[0.001]	[0.000]			
Observations	10859	10859	10859	10859	10859	10859
Emotional Stability (standardized) 2023						
Treatment Assigned	0.010	0.052*	0.051*	0.016	0.079*	0.078*
	(0.816)	(0.068)	(0.065)	(0.815)	(0.067)	(0.064)
	[0.853]	[0.190]	[0.215]			
Observations	7976	7976	7976	7976	7976	7976
Locus of Control (standardized) 2022						
Treatment Assigned	0.066***	0.067***	0.067***	0.082***	0.083***	0.083***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]			
Observations	10859	10859	10859	10859	10859	10859
Locus of Control (standardized) 2023						
Treatment Assigned	-0.001	0.001	0.002	-0.001	0.002	0.003
	(0.976)	(0.955)	(0.933)	(0.976)	(0.955)	(0.932)
	[0.972]	[0.938]	[0.909]			
Observations	7976	7976	7976	7976	7976	7976
Degree Controls		X	X		X	X
Diploma Controls		X	X		X	X
Gender Controls		X	X		X	X
Economic Controls			X			X
Randomization Reps:	1000					

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6.3.2 Effects on Expectations

Table 9 and 10 report results of the analysis of treatment effects on expectations. The tables have the same structure as before, with both ITT and LATE estimates presented. Overall, effects are smaller in magnitude and more frequently insignificant than in the analysis of the spillover effects on non-cognitive skills. However, the direction of the effects seems to be broadly consistent with what would be expected from the intervention. Point estimates for a dummy capturing whether a student wants to continue their studies after graduation or enter the labor market are negative for the 2022 sample and mixed for the 2023 sample, though insignificantly so. For the 2022 sample, this would be in line with the idea that the intervention improves students confidence to enter the labor market. Coefficients on log expected salary are close to zero and insignificant for the 2022 sample. For the 2023 sample, they emerge as positive and significant at the 10% level. Given the documented imbalances however, this suprisingly large effect should be interpreted with caution. For the 2022 sample, the intervention seems to have had a slightly positive impact on the expected 6-month job-find probability with small but significant point estimates. However, while p-values are below the 5% threshold for some coefficients, randomization inference p-values are not, indicating that the observed effect might be due to the specific observed randomization. Point estimates for the 2023 sample are positive but insignificant. Similarly, for the 2022 sample, the intervention seems to have significantly improved students perceived preparedness for job-search, with effects reaching up to 5% of a standard deviation per year of treatment. Again, some of the randomization inference p-values go slightly above the 10% threshold. More striking is, that point estimates for the 2023 sample consistently point in the other direction, however remaining insignificant. With regards to the perceived probability of liking the first job, effects seem to be positive for both years, with both samples displaying significant coefficients. Point estimates for the coefficients on expected probability of securing a permanent contract are negative across both years but largely insignificant.

To relate the results collected here to the descriptive survey evidence discussed above, note that among the five expectations variables considered here, it is those displaying significant effects for the 2022 sample, that were shown to be more strongly correlated to non-cognitive skills. Table 5 showed that while non-cognitive skills are only limited predictors of study decisions and expected income, they have strong predictive power for expected employment and the probability of liking the job, and a strong link with the perceived preparedness for job-search. A possible explanation for this could be that the intervention impacted expectations through its impact on non-cognitive skills. While beyond the scope of this paper, investigating the mediating effect of non-cognitive skills on expectation in the context of this intervention could be interesting.

Table 9: Expectations

Part 1: Expectations

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Continue Studies Yes (2022)						
Treatment Assigned	-0.004	-0.008	-0.007	-0.005	-0.010	-0.009
	(0.599)	(0.280)	(0.315)	(0.593)	(0.264)	(0.301)
	[0.643]	[0.310]	[0.321]			
Observations	10859	10859	10859	10859	10859	10859
Continue Studies Yes (2023)						
Treatment Assigned	0.010	0.001	-0.003	0.016	0.001	-0.004
	(0.653)	(0.966)	(0.870)	(0.650)	(0.965)	(0.869)
	[0.506]	[0.942]	[0.816]			
Observations	7976	7976	7976	7976	7976	7976
Log Expected Salary (2022)						
Treatment Assigned	-0.002	-0.001	0.001	-0.003	-0.001	0.002
	(0.849)	(0.954)	(0.906)	(0.848)	(0.954)	(0.905)
	[0.832]	[0.944]	[0.905]			
Observations	10825	10825	10825	10825	10825	10825
Log Expected Salary (2023)						
Treatment Assigned	0.026	0.040*	0.037*	0.040	0.061*	0.056*
	(0.331)	(0.058)	(0.082)	(0.335)	(0.052)	(0.076)
	[0.363]	[0.016]	[0.012]			
Observations	7955	7955	7955	7955	7955	7955
Subjective 6-Month Job-Find Probability (2022)						
Treatment Assigned	0.007*	0.009**	0.008**	0.009*	0.011**	0.010**
	(0.082)	(0.022)	(0.022)	(0.071)	(0.017)	(0.018)
	[0.281]	[0.160]	[0.136]			
Observations	10859	10859	10859	10859	10859	10859
Subjective 6-Month Job-Find Probability (2023)						
Treatment Assigned	0.004	0.003	0.001	0.006	0.005	0.002
	(0.740)	(0.731)	(0.897)	(0.740)	(0.730)	(0.897)
	[0.972]	[0.933]	[0.933]			
Observations	7976	7976	7976	7976	7976	7976
Degree Controls		X	X		X	X
Diploma Controls		X	X		X	X
Gender Controls		X	X		X	X
Economic Controls			X			X
Randomization Reps:	1000					

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Expectations

Part 2: Expectations

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Preparedness for Job-Search (2022)						
Treatment Assigned	0.042***	0.045***	0.041***	0.053***	0.056***	0.051***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
	[0.021]	[0.018]	[0.010]			
Observations	10859	10859	10859	10859	10859	10859
Preparedness for Job-Search (2023)						
Treatment Assigned	-0.013	-0.027	-0.029	-0.019	-0.042	-0.045
	(0.716)	(0.397)	(0.346)	(0.713)	(0.387)	(0.332)
	[0.726]	[0.172]	[0.156]			
Observations	7976	7976	7976	7976	7976	7976
Probability of Liking Job (2022)						
Treatment Assigned	0.008*	0.010***	0.009***	0.010*	0.012***	0.011***
	(0.060)	(0.004)	(0.006)	(0.054)	(0.003)	(0.004)
	[0.218]	[0.028]	[0.023]			
Observations	10859	10859	10859	10859	10859	10859
Probability of Liking Job (2023)						
Treatment Assigned	0.010	0.017**	0.018**	0.015	0.026**	0.028**
	(0.308)	(0.038)	(0.031)	(0.312)	(0.043)	(0.036)
	[0.347]	[0.062]	[0.078]			
Observations	7976	7976	7976	7976	7976	7976
Expect Permanent Contract (2022)						
Treatment Assigned	-0.010*	-0.009	-0.009	-0.012*	-0.011	-0.011
	(0.091)	(0.115)	(0.129)	(0.092)	(0.115)	(0.128)
	[0.077]	[0.089]	[0.091]			
Observations	10859	10859	10859	10859	10859	10859
Expect Permanent Contract (2023)						
Treatment Assigned	-0.008	-0.009	-0.012	-0.012	-0.014	-0.018
	(0.566)	(0.517)	(0.367)	(0.565)	(0.516)	(0.366)
	[0.452]	[0.469]	[0.509]			
Observations	7976	7976	7976	7976	7976	7976
Degree Controls		X	X		X	X
Diploma Controls		X	X		X	X
Gender Controls		X	X		X	X
Economic Controls			X			X
Randomization Reps:	1000					

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Robustness

The appendix in section 9 includes tables reporting the results of the same robustness checks on the expectations variables that were performed before on non-cognitive skills (Continue Studies Yes (C7), Log Expected Salary (C8), Subj. 6-Month Job-Find Probability (C9), Preparedness for Job-Search (C10), Probability of Liking Job (C11), Expected Probability of Securing Permanent Contract (C12)). As for the non-cognitive skills, estimates seem to be largely robust to changes in the aggregation of the degree variable as well as to the exclusion of the fastest 5% of responders.
The results for the 2022 sample however do change when excluding schools in Grand-Est and Pays de la Loire that were randomized in strata of four. The coefficients for continue studies become more negative and significant at higher levels, even though randomization inference p-values remain insignificant. Point estimates for log expected salary become negative, though with insignificant p-values but partly significant randomization inference p-values. This in a way is more what would have been expected if the intervention indeed had a correcting effect on students' salary expectations, which are assumed to be overoptimistic on average. Coefficients for the subjective 6-month job-find probability increase in magnitude under the exclusion and remain significant at similar levels. The same is the case for the preparedness of job-search and the expected probability of liking a job.
The results under the exclusion of incomplete pairs are again more difficult to interpret. Overall however, little changes with the exception of the estimates for the subjective 6-month job-find probability and the perceived preparedness. While estimates for the 2022 sample remain mostly stable, the results for the 2023 sample become more negative in magnitude, and hence are across the board even further away from the 2022 estimates, something that seems to be tough to rationalize, unless somehow, the intervention's effect has been different over the years or the results for the 2023 sample are strongly impacted by not controlled for imbalances.

6.4 Heterogeneous Treatment Effects

Given the discussion about different endowments of non-cognitive skills across gender and the fact, that men and women seem to have different expectations, it is also analyzed whether the intervention has heterogeneous effects on the two groups. In order not to have to report all the balancing tests again, results are reported under the full set of controls used for the previous regressions, including degree, diploma and local economic controls. While this does not guarantee to control for all possible imbalances, it is the best set of controls available and should cover most imbalances found for the full sample.

Appendix Table C13 and C14 report the effects of the intervention on non-cognitive skills separately for men an women. Overall, men appear as the drivers behind the effects discussed before, exhibiting larger and significant coefficients more often. Men and women display significant effects for Extraversion in the 2022 sample, with point estimates being higher for men. The effects on Agreeableness remain relatively stable and significant across both years for men. With the exception of open-mindedness, that did not emerge as significant in the previous discussion as well, most of the other non-cognitive skills also appear to have relatively stable coefficient sizes across year and gender. The biggest difference by year and gender emerges for Locus of Control where effects are strong for both gender in the 2022 sample and virtually absent in the 2023 sample. In the sense that most coefficients seem to be coherent across years and gender, I interpret this analyses as another successful robustness check on the previous conclusions reached.

When comparing the coefficients by gender within year of randomization, it is noticeable that the coefficients for men are consistently of higher magnitude than womens' when significant. The increases in Agreeableness and Conscientiousness that are documented for men across both randomization years might contribute to closing the gap in those skills with respect to women, while the effects on Extraversion, Emotional Stability and Locus of Control seem to increase the gap.

Appendix Tables C15 and C16 report results of heterogeneous effects on expectations. As in the analysis on the full sample, fewer significant effects emerge. The increase in subjective 6-month job-find probability previously documented seems to again be driven by men at schools randomized in 2022. The treatment further seems to positively impact perceived preparedness for job-search for 2022 school students across gender. For the 2023 sample, insignificant negative coefficients emerge across gender. The gendered effects on probability of liking the first job also seem to be difficult to interpret. While all coefficients are positive, across year and gender, effects for women are small and insignificant for 2022 and large and significant for 2023 school students, while effects for men are small in magnitude across both years and only significant for 2022. The effect of the intervention on the probability of expecting to receive a permanent contract is significantly negative in both randomization samples for women. Point estimates for men are negative as well, but of smaller magnitude and insignificant.

7 Discussion

While other studies do find effects of career interventions on non-cognitive skills (Carlana et al. 2022) and interventions directly aimed at non-cognitive skills have consistently improved the same (e.g. Sorrenti et al. 2024) the results documented above are surprising on multiple levels. Most importantly, effect sizes on non-cognitive skills discussed above are large, especially given that the students answering the survey did not receive the intervention directly themselves. At the same time, while effect sizes on non-cognitive skills are documented to be large, the effects on expectations are comparably small, albeit present for some of the expectations variables and in some of the robustness specifications. While surprising, the effects on non-cognitive skills in the analysed sample are remarkably robust to the changes performed. Significant effects were present across specifications and coefficient sizes were mostly insensitive to the inclusion of different sets of controls. Most of the effects on non-cognitive skills were furthermore robust to changes in the sample (excluding Grand-Est and Pays de la Loire; excluding incomplete strata) and to gender level analysis. The latter also showed that men drive most of the effects, and that effects for them were consistently present and significant in both randomization samples.

While the results were largely robust to the checks performed, it might still be that the samples are imbalanced across unobserved variables. Further, given that only a fraction of schools and students responded to the survey, it cannot be ruled out that differential selection into response is driving effects. These concerns as well as potential mechanisms driving spillover are discussed now.

7.1 Potential Mechanisms driving Spillover Effects

To rationalize the results, it is necessary to discuss the channel through which the intervention might have spilled over on students today. I propose three potential mechanism: peer effects, teacher effects and school management effects.

Peer effects:

Students that are graduating from a CAP or BacPro diploma in 2024 will have been at the vocational school since the 2022/2023 and 2021/2022 school year respectively. They hence have been at the school for up to two years during which their seniors received the intervention. Assuming that students interact across school years, information sharing might be a channel that directly impacts students today.

Teacher effects:

Some of the teachers that have participated in the intervention for up to two years are teaching students responding to the survey. They interacted with the France Travail case workers and local agencies, learned about which aspects of the intervention students enjoyed and will have formed an opinion about which methods worked well and which did not. Students enrolled in their final year in 2023/2024 will hence have been exposed to up to two years of classes with teachers who have participated in the previous interventions. This may very well have a positive influence on the teaching quality and content of classes.

School management:

The intervention might furthermore impact decisions taken by school management. Changes in investment and hiring decisions or changes in overall management mentality could impact how students perceive their future chances and how they see themselves.

With the currently available data, these mechanisms cannot be tested. It would be interesting to survey teachers and school managers to investigate further how they change their behavior after the intervention to shed light on this.

7.2 Limitations

Concern 1: Limited individual level control variables

The main caveat in the analysis of the present sample is the lack of individual level control variables. Only gender and degree could be controlled for at the individual level of survey respondents so far. All other controls were aggregated at the school level and included the composition of nationality, socio-economic status and gender in previous cohorts. While this allows to draw conclusions on the balance of schools assigned to treatment and control in previous cohorts, it only has a limited relevance to the balance of the sample at hand. With more individual level data like students grades over the years, including those from before joining the vocational school, students socio-economic background and nationality, more general conclusions about the robustness of the documented effects could be found. More individual level variables would also be integral to better understand which students respond to the survey and which among them, if any, exhibit effects. All that said, the lack of individual control

variables does not necessarily invalidate the previous results. Local economic indicators for example should be good proxies of student level socio-economic variables and previous cohort information is likely highly correlated with current year's one. Furthermore, gender and the fine degree categories capture significant individual heterogeneity as degree choice is probably correlated with a large variety of individual characteristics.

Concern 2: Demand effects

Another channel that could drive the effect sizes is a potential experimenter demand effect, where students at treated schools are aware of the survey being linked to the treatment that their peers in previous years received and that they will receive themselves. The fact that schools that received the treatment respond to the survey more often could be read as an indication for the potential presence of this demand effect on the school level. Whether students indeed felt an experimenter demand, maybe transmitted by the way teachers introduced the survey to them, is tough to investigate. One potential proxy, the time taken to respond to the survey, does not indicate that students at treated schools spent more time on the survey than their peers at untreated schools. If this were the case, it could be linked to students more thoroughly thinking about their answers because the survey is taken more seriously overall. However, it could still be that students responded to the questions in a more positive mindset or felt that certain responses were expected from them, knowing that they are at a school that has previously been treated.

Concern 3: Absolute Response Rate and Differential Attrition

Beyond the concerns with respect to the internal validity of the results, meaning the results inferred from the students for whom responses were recorded, there is a more serious concern with respect to external validity. One reason why the effect sizes among non-attriters was found to be so high could be that attrition from survey response and potential outcomes are related. This would mean that assumption 2 and potentially 3, outlined in section 6.1.3 might not hold. These assumptions require that attrition and potential outcomes are independent, or independent conditional on some covariates (respectively assumption 2 and 3). An example of how this could be violate in practice would be if schools who have low potential outcomes, i.e. would not profit from the intervention as much as others, are less likely to respond to the survey. In order to further investigate this issue and open a discussion for future steps, I use so called Lee bounds (Lee 2009), following the implementation by McKenzie 2024 and McKenzie 2017. This approach allows me to estimate bounds of the true treatment effect in the presence of attrition. It relies on the assumption of random treatment assignment, given by design in this context, and monotonicity of attrition. Monotinicity here refers to the assumption that treatment assignment only increases the likelihood of responding to the survey and never decreases it. This assumption seems likely to hold in the surveys context as treatment, if anything, should motivate schools to report results to the survey, given the school's prior contact with the researchers.

To exemplify how differential attrition can impact the tightness of the bounds for the treatment effect, Table 11 presents results for bounds taking into account within-school attrition and overall student attrition (as defined before). I decided to use Locus of Control and Agreeablness as the dependent variables as they emerged as highly significant and large in magnitude outcome variables in the previous analysis.

I construct the Lee bounds following McKenzie 2024 and McKenzie 2017. To estimate the lower

bound, the highest values of the outcome variable for treated students are trimmed. To estimate the higher bound, the lowest values of the outcome variable for treated students are trimmed. The trim rate is calculated as follows: the difference between attrition rate among the treated and the control divided by the attrition rate among the treated. So the higher the difference between the attrition rates between treated and control, the more is trimmed. The question the bounds help investigate is what the treatment effect would be if all those that answered more among the treated were those with the highest or lowest values of the outcome variable respectively. If the lower bound was positive and significant, it would be possible to add reason to the conclusion, that the treatment effect among those who do not attrite is indeed positive.
Table 11 and table 12 present the bounds. As documented before, differential attrition in the 2022 sample was much smaller than in the 2023 sample. Especially the within responding school attrition of students was small, leading to bounds that are tight around the previous estimates for the 2022 sample. When considering the overall differential attrition, where the difference between treated and control was bigger, the bounds around the effects for both Locus of Control and Agreeableness do include zero for the 2022 sample. This shows that even though the difference in overall attrition for the 2022 sample was only 2.8 percentage points, the treatment effect might not be positive under the extreme assumptions made. As expected, the bounds for the 2023 sample are even larger, driven by the high differential attrition rates.
For the overall attrition, the bounds assume that either the top or bottom 11.86% of treated students should be trimmed to make the treated sample equal to the control sample. This is a strong assumption, as it would imply that selection into survey response is strongly driven by factors predicting high or low values of the dependent variables. For the 2022 sample however, I have shown before that at least the available variables, that would be the same that are strongly correlated with the outcomes, do not strongly predict response. While it is definitely possible that there are other unobserved predictors, this underlines the severity of the assumption, but also shows how sensitive the results are to the assumption that attrition is not correlated to treatment assignment. The easiest solution to deal with this concern would be to collect more responses from both treated and control schools, thereby decreasing the overall attrition rate and gaining statistical power. However, this is could potentially lead to further selection. Otherwise, investigating whether individual characteristic not available at the moment predict attrition when interacted with treatment assignment would allow for a better understanding of the extent of this problem.

8 Conclusion

In 2022 and 2023, around half of French vocational schools participated in an intervention by the French employment agency aimed at facilitating students' integration into the labor market after graduation. This study analyzed the spillover effects of the intervention on the expectations and non-cognitive skills of current final-year students at these schools, using a large-scale survey.

The survey data revealed that students at control schools (those not directly receiving the intervention) exhibit significant gender differences in non-cognitive skills and expectations. Men displayed higher levels of extraversion, emotional stability and locus of control, while women showed higher levels of conscientiousness, open-mindedness, and agreeableness. Additionally, men reported higher expectations for quicker employment, better job satisfaction, higher salaries, and more permanent contracts compared to women. Further analysis revealed, that non-cognitive skills are strong predictors of students'

labor market expectations within the sample of vocational students. Given this and the differences in skill endowments across gender, differences in expectations could be descriptively disentangled.

Leveraging the random assignment of schools to the intervention, the analysis found evidence suggesting that the intervention had spillover effects on students' non-cognitive skills and expectations. The results indicate that scores on four out of five personality traits and locus of control increased significantly, with notable gender differences showing men experiencing stronger effects. Expectations were impacted mostly in the direction expected given the interventions content. It was not possible to infer however, whether expectations became more realistic, something that will be investigated with outcome data in the future. The results were robust across various specifications and checks. Possible channels for these spillover effects include senior peers sharing information, improved teaching methods by teachers, and organizational changes by school management.

However, the external validity of the findings is constrained by a limited number of individual-level covariates and potential biases in survey response selection. Several methods were discussed to assess the extent of these limitations, including robustness checks and alternative model specifications.

The survey will be repeated after the students themselves receive the intervention, providing a more comprehensive analysis of the intervention's direct effects. This follow-up study will be crucial for addressing the current findings and validating the initial results. It will also be important to consider the possible spillover effects observed in this study when analyzing the new data. Incorporating additional individual-level controls as they become available will further enhance the robustness of these future analyses. Moreover, tracking students' professional trajectories in the coming years will be essential to understand how their expectations and non-cognitive skills translate into actual labor market outcomes, thereby offering deeper insights into the long-term impact of the intervention.

These insights are highly relevant for policymakers and educators, as they highlight channels through which expectations and non-cognitive skills maybe impacted in the context of vocational education. Addressing the gender expectations gap is particularly important, as it may influence different outcomes for men and women in the labor market. The findings suggest that targeted interventions can have substantial positive effects, not only on direct participants but also on their peers, thereby offering a scalable approach to enhancing vocational education and labor market integration.

Table 11: Lee Bounds for Treatment Effects: Locus of Control

Dependent Variable: Locus of Control (standardized)

	(1) Lower Bound (OLS)	(2) Lower Bound (IV)	(3) Upper Bound (OLS)	(4) Upper Bound (IV)
2022 within school attrition: Trim rate .0046				
Treatment Assigned	0.063***	0.079***	0.075***	0.094***
	(0.011)	(0.014)	(0.011)	(0.015)
Observations	10833	10833	10834	10834
2023 within school attrition: Trim rate .24698				
Treatment Assigned	-0.401***	-0.610***	0.438***	0.673***
	(0.025)	(0.081)	(0.023)	(0.085)
Observations	6811	6811	6812	6812
2022 overall attrition: Trim rate .1186				
Treatment Assigned	-0.036***	-0.046***	0.184***	0.230***
	(0.010)	(0.013)	(0.010)	(0.020)
Observations	10191	10191	10192	10192
2023 overall attrition: Trim rate .2913				
Treatment Assigned	-0.468***	-0.711***	0.501***	0.769***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	6602	6602	6603	6603

Note: The trim rate relates to the percentiles dropped from the dependent variable for the treated group. It is calculated as (attrition rate treated - attrition rate control) / (attrition rate treated). All regressions include gender, degree and economic controls. Robust standard errors were clustered at the strata level. P-values are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Lee Bounds for Treatment Effects: Agreeableness

Dependent Variable: Agreeableness (standardized)

	(1) Lower Bound (OLS)	(2) Lower Bound (IV)	(3) Upper Bound (OLS)	(4) Upper Bound (IV)
2022 within school attrition: Trim rate .0046				
Treatment Assigned	0.045***	0.057***	0.056***	0.070***
	(0.012)	(0.016)	(0.012)	(0.017)
Observations	10833	10833	10834	10834
2023 within school attrition: Trim rate .24698				
Treatment Assigned	-0.330***	-0.509***	0.500***	0.761***
	(0.030)	(0.078)	(0.027)	(0.095)
Observations	6811	6811	6812	6812
2022 overall attrition: Trim rate .1186				
Treatment Assigned	-0.044***	-0.055***	0.164***	0.205***
	(0.012)	(0.015)	(0.011)	(0.020)
Observations	10191	10191	10192	10192
2023 overall attrition: Trim rate .2913				
Treatment Assigned	-0.395***	-0.609***	0.565***	0.862***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	6602	6602	6603	6603

Note: The trim rate relates to the percentiles dropped from the dependent variable for the treated group. It is calculated as (attrition rate treated - attrition rate control) / (attrition rate treated). All regressions include gender, degree and economic controls. Robust standard errors were clustered at the strata level. P-values are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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Table A1: Representativeness of Participating Schools

	(1) Not Participating		(2) Participating		(3) Difference	
	Mean	SD	Mean	SD	Difference	p-value
School Performance (INSERJEUNE 2022)						
Share Continuing Studies After Graduation (19/20)	47.49	7.94	48.35	7.62	-0.86	(0.032)
Share Continuing Studies After Graduation (20/21)	49.17	7.87	49.62	7.51	-0.45	(0.255)
Share Continuing Studies After Graduation (21/22)	49.96	7.82	50.42	7.55	-0.46	(0.241)
Share Employed 6 Months After Graduation (19/20)	38.50	12.76	35.63	11.15	2.87	(0.000)
Share Employed 6 Months After Graduation (20/21)	38.61	12.72	36.50	11.13	2.11	(0.001)
Share Employed 6 Months After Graduation (21/22)	44.79	12.43	43.61	10.50	1.18	(0.047)
Value Added 6 Months After Graduation (19/20)	0.69	5.76	-0.98	5.32	1.66	(0.000)
Value Added 6 Months After Graduation (20/21)	0.42	5.66	-0.35	5.28	0.78	(0.006)
Value Added 6 Months After Graduation (21/22)	0.06	5.53	0.31	5.12	-0.25	(0.361)
Share Employed 12 Months After Graduation (19/20)	46.12	12.86	43.89	11.83	2.24	(0.001)
Share Employed 12 Months After Graduation (20/21)	49.80	13.14	47.64	11.55	2.16	(0.001)
Share Employed 18 Months After Graduation (19/20)	49.18	11.57	47.53	10.21	1.64	(0.004)
Share Employed 24 Months After Graduation (19/20)	56.37	11.79	54.59	10.18	1.78	(0.002)
Local Unemployment	7.92	3.32	7.16	1.58	0.75	(0.000)
Median Local Living Standard (Euro)	22317.57	2900.13	22603.65	2182.40	-286.09	(0.031)
Top to Bottom Decile Living Standard Ratio	3.40	0.78	3.31	0.70	0.09	(0.027)
Summary: 2022/2023 (BCS 2022)						
Number of Students (BCS)	103.53	68.20	111.86	52.79	-8.33	(0.007)
Number of Male Students (BCS)	65.07	47.89	66.12	39.37	-1.05	(0.639)
Number of Female Students (BCS)	38.46	39.53	45.74	40.10	-7.28	(0.000)
Share of Male Students (BCS)	64.46	25.16	61.06	26.00	3.39	(0.010)
Share of Female Students (BCS)	35.54	25.16	38.94	26.00	-3.39	(0.010)
Men to Women Ratio (BCS)	7.84	17.18	7.29	15.75	0.55	(0.521)
Average Age of Students (BCS)	17.35	0.28	17.37	0.19	-0.02	(0.085)
Nationalities: 2022/2023 (BCS 2022)						
Share French Nationality (BCS)	87.69	11.37	86.38	9.60	1.31	(0.014)
Share European (EU) Nationality (BCS)	2.65	3.66	2.94	3.13	-0.29	(0.095)
Share European (outside EU) Nationality (BCS)	0.75	1.39	1.32	1.89	-0.57	(0.000)
Share Asian Nationality (BCS)	1.67	2.49	2.20	2.43	-0.52	(0.000)
Share African Nationality (BCS)	5.95	8.52	6.74	6.44	-0.79	(0.040)
Share American Nationality (BCS)	1.27	5.08	0.41	0.80	0.85	(0.000)
Share Oceanic Nationality (BCS)	0.00	0.06	0.00	0.05	0.00	(0.835)
Share Nationality not defined (BCS)	0.02	0.18	0.02	0.13	0.00	(0.651)
Parents PCS: 2022/2023 (BCS 2022)						
Share Agriculture (BCS)	1.11	2.28	0.81	1.43	0.30	(0.002)
Share Artisans, Merchants, and Entrepreneurs (BCS)	8.22	5.21	7.44	3.88	0.77	(0.001)
Share Executive Employees (Cadre) (BCS)	6.27	5.47	5.70	4.35	0.57	(0.022)
Share Intermediary Professions (BCS)	9.42	5.65	9.50	4.07	-0.08	(0.756)
Share Employees (BCS)	17.86	7.69	17.55	6.20	0.31	(0.385)
Share Workers (BCS)	31.71	11.42	34.69	8.70	-2.99	(0.000)
Share Retirees (BCS)	2.09	1.91	2.06	1.76	0.03	(0.775)
Share Unemployed/Inactives (BCS)	18.35	13.58	16.76	8.12	1.59	(0.005)
Share Unknown or no Subject (BCS)	4.98	5.50	5.49	4.81	-0.51	(0.053)
Observations	821		712		1533	

NOTE: This table compares schools included in the experiment (either as control or treatment) with schools not included in the experiment.

Table A2: Balance of Treatment Assignment in 2022 (School Level)

	(1) Control Assignment		(2) Treatment Assignment		(3) Difference	
	Mean	SD	Mean	SD	Difference	p-value
Student Field of Study: 2023/2024 (DEPP 2024)						
Share Other Occupations	15.66	24.46	15.41	23.56	0.25	(0.918)
Share Construction	7.74	17.45	9.76	17.48	-2.02	(0.255)
Share Electrotechnics and Energie	21.00	28.65	21.40	26.75	-0.40	(0.886)
Share Client Services	21.50	26.32	19.87	24.80	1.63	(0.528)
Share Hotel and Restaurations	10.07	22.09	9.22	20.53	0.85	(0.695)
Share Administrative Services	8.42	15.46	8.70	16.73	-0.27	(0.868)
Share Woodwork and Furniture	3.35	12.45	2.67	7.70	0.68	(0.513)
Share Logistics, Transport and Maintenance	7.75	16.89	8.48	19.91	-0.73	(0.697)
Share Industrial Maintenance	2.09	6.90	2.86	11.64	-0.77	(0.432)
Share Fashion, Clothing and Leather	2.43	7.35	1.64	6.98	0.78	(0.281)
School Performance (INSERJEUNE 2022)						
Share Continuing Studies After Graduation (19/20)	46.72	7.18	47.36	7.76	-0.64	(0.400)
Share Continuing Studies After Graduation (20/21)	48.91	7.31	48.74	7.41	0.17	(0.818)
Share Continuing Studies After Graduation (21/22)	50.01	7.45	49.93	6.90	0.08	(0.907)
Share Employed 6 Months After Graduation (19/20)	37.38	11.21	37.75	10.54	-0.37	(0.740)
Share Employed 6 Months After Graduation (20/21)	37.92	11.36	39.03	10.99	-1.11	(0.328)
Share Employed 6 Months After Graduation (21/22)	44.42	11.04	45.54	9.89	-1.12	(0.293)
Value Added 6 Months After Graduation (19/20)	-0.07	5.63	-1.02	4.85	0.95	(0.073)
Value Added 6 Months After Graduation (20/21)	0.22	5.45	-0.16	5.17	0.38	(0.483)
Value Added 6 Months After Graduation (21/22)	0.22	5.40	0.46	5.10	-0.24	(0.652)
Share Employed 12 Months After Graduation (19/20)	45.60	12.24	46.34	11.08	-0.74	(0.531)
Share Employed 12 Months After Graduation (20/21)	49.06	11.70	50.13	11.07	-1.07	(0.356)
Share Employed 18 Months After Graduation (19/20)	48.37	10.52	49.61	9.38	-1.24	(0.218)
Share Employed 24 Months After Graduation (19/20)	55.59	10.57	56.65	9.76	-1.06	(0.302)
Local Unemployment	6.91	1.34	6.93	1.40	-0.02	(0.892)
Median Local Living Standard (Euro)	22495.64	1841.03	22486.94	1793.90	8.70	(0.963)
Top to Bottom Decile Living Standard Ratio	3.20	0.57	3.20	0.55	-0.00	(0.961)
Summary: 2022/2023 (BCS 2022)						
Number of Students (BCS)	107.39	54.19	111.37	49.92	-3.98	(0.451)
Number of Male Students (BCS)	62.18	37.74	68.25	37.90	-6.07	(0.115)
Number of Female Students (BCS)	45.21	43.17	43.12	37.38	2.10	(0.608)
Share of Male Students (BCS)	60.84	25.69	63.77	24.76	-2.93	(0.253)
Share of Female Students (BCS)	39.16	25.69	36.23	24.76	2.93	(0.253)
Men to Women Ratio (BCS)	7.07	16.19	6.57	12.61	0.50	(0.740)
Average Age of Students (BCS)	17.37	0.19	17.38	0.17	-0.01	(0.635)
Nationalities: 2022/2023 (BCS 2022)						
Share French Nationality (BCS)	86.74	9.65	86.36	9.26	0.38	(0.693)
Share European (EU) Nationality (BCS)	2.95	3.17	2.94	3.06	0.00	(0.997)
Share European (outside EU) Nationality (BCS)	1.47	1.92	1.60	2.37	-0.13	(0.557)
Share Asian Nationality (BCS)	2.32	2.47	2.26	2.83	0.05	(0.839)
Share African Nationality (BCS)	6.21	6.61	6.47	5.84	-0.26	(0.680)
Share American Nationality (BCS)	0.30	0.65	0.32	0.69	-0.02	(0.780)
Share Oceanic Nationality (BCS)	0.00	0.05	0.00	0.06	-0.00	(0.826)
Share Nationality not defined (BCS)	0.01	0.07	0.03	0.18	-0.02	(0.090)
Parents PCS: 2022/2023 (BCS 2022)						
Share Agriculture (BCS)	0.87	1.42	0.80	1.30	0.07	(0.636)
Share Artisans, Merchants, and Entrepreneurs (BCS)	7.47	4.00	7.94	3.64	-0.47	(0.224)
Share Executive Employees (Cadre) (BCS)	5.72	3.87	6.24	4.64	-0.53	(0.227)
Share Intermediary Professions (BCS)	9.63	4.18	9.97	4.30	-0.34	(0.425)
Share Employees (BCS)	16.93	6.38	16.97	6.16	-0.04	(0.954)
Share Workers (BCS)	36.01	9.77	34.35	8.43	1.66	(0.073)
Share Retirees (BCS)	1.87	2.03	1.88	1.68	-0.01	(0.975)
Share Unemployed/Inactives (BCS)	16.12	7.99	16.15	8.13	-0.03	(0.969)
Share Unknown or no Subject (BCS)	5.38	5.10	5.69	5.53	-0.31	(0.570)
Observations	205		185		390	

Table A3: Balance of Treatment Assignment in 2023 (School Level)

	(1) Control Assignment		(2) Treatment Assignment		(3) Difference	
	Mean	SD	Mean	SD	Difference	p-value
Student Field of Study: 2023/2024 (DEPP 2024)						
Share Other Occupations	16.72	25.10	18.45	27.84	-1.72	(0.560)
Share Construction	9.22	17.48	8.64	17.52	0.58	(0.766)
Share Electrotechnics and Energie	21.93	29.07	15.92	25.83	6.00	(0.051)
Share Client Services	19.54	26.90	19.59	26.00	-0.06	(0.984)
Share Hotel and Restaurations	8.72	20.86	12.63	25.22	-3.91	(0.130)
Share Administrative Services	7.68	13.87	9.42	18.58	-1.75	(0.339)
Share Woodwork and Furniture	3.20	11.22	3.68	11.25	-0.47	(0.706)
Share Logistics, Transport and Maintenance	7.22	17.65	6.74	18.04	0.49	(0.807)
Share Industrial Maintenance	1.58	5.31	1.82	5.90	-0.24	(0.699)
Share Fashion, Clothing and Leather	4.20	12.01	3.12	8.60	1.09	(0.354)
School Performance (INSERJEUNE 2022)						
Share Continuing Studies After Graduation (19/20)	50.88	7.40	49.07	7.53	1.81	(0.030)
Share Continuing Studies After Graduation (20/21)	51.33	7.29	49.88	7.84	1.45	(0.086)
Share Continuing Studies After Graduation (21/22)	51.47	8.10	50.48	7.78	0.98	(0.268)
Share Employed 6 Months After Graduation (19/20)	33.65	11.44	32.96	10.68	0.69	(0.577)
Share Employed 6 Months After Graduation (20/21)	34.56	11.17	33.75	10.09	0.81	(0.497)
Share Employed 6 Months After Graduation (21/22)	42.09	10.50	41.87	10.08	0.22	(0.846)
Value Added 6 Months After Graduation (19/20)	-1.16	5.33	-1.88	5.31	0.71	(0.230)
Value Added 6 Months After Graduation (20/21)	-0.41	5.32	-1.23	5.09	0.83	(0.156)
Value Added 6 Months After Graduation (21/22)	0.52	4.98	0.07	4.96	0.45	(0.417)
Share Employed 12 Months After Graduation (19/20)	41.00	11.78	41.77	11.31	-0.77	(0.551)
Share Employed 12 Months After Graduation (20/21)	45.10	11.53	45.49	11.10	-0.39	(0.756)
Share Employed 18 Months After Graduation (19/20)	46.06	10.33	45.57	10.13	0.50	(0.664)
Share Employed 24 Months After Graduation (19/20)	52.69	9.97	52.82	9.81	-0.13	(0.904)
Local Unemployment	7.50	1.78	7.42	1.75	0.08	(0.685)
Median Local Living Standard (Euro)	22646.33	2481.06	22827.13	2619.62	-180.81	(0.525)
Top to Bottom Decile Living Standard Ratio	3.44	0.80	3.46	0.83	-0.02	(0.817)
Summary: 2022/2023 (BCS 2022)						
Number of Students (BCS)	114.32	54.52	115.68	52.51	-1.36	(0.820)
Number of Male Students (BCS)	69.86	43.06	65.02	39.13	4.84	(0.294)
Number of Female Students (BCS)	44.46	37.20	50.65	41.71	-6.20	(0.161)
Share of Male Students (BCS)	61.50	26.46	57.85	27.16	3.65	(0.224)
Share of Female Students (BCS)	38.50	26.46	42.15	27.16	-3.65	(0.224)
Men to Women Ratio (BCS)	8.00	17.48	7.67	16.62	0.33	(0.864)
Average Age of Students (BCS)	17.38	0.19	17.35	0.21	0.02	(0.279)
Nationalities: 2022/2023 (BCS 2022)						
Share French Nationality (BCS)	85.99	10.12	86.33	9.46	-0.34	(0.758)
Share European (EU) Nationality (BCS)	2.76	2.88	3.09	3.39	-0.33	(0.346)
Share European (outside EU) Nationality (BCS)	0.99	1.35	1.12	1.63	-0.13	(0.430)
Share Asian Nationality (BCS)	2.04	2.11	2.11	2.19	-0.07	(0.783)
Share African Nationality (BCS)	7.72	7.22	6.75	6.01	0.96	(0.197)
Share American Nationality (BCS)	0.50	0.87	0.57	0.98	-0.07	(0.499)
Share Oceanic Nationality (BCS)	0.00	0.00	0.00	0.05	-0.00	(0.319)
Share Nationality not defined (BCS)	0.00	0.00	0.02	0.17	-0.02	(0.126)
Parents PCS: 2022/2023 (BCS 2022)						
Share Agriculture (BCS)	0.79	1.66	0.74	1.32	0.06	(0.731)
Share Artisans, Merchants, and Entrepreneurs (BCS)	7.08	3.97	7.19	3.86	-0.11	(0.801)
Share Executive Employees (Cadre) (BCS)	4.93	3.84	5.78	4.94	-0.85	(0.087)
Share Intermediary Professions (BCS)	9.08	4.07	9.19	3.63	-0.11	(0.804)
Share Employees (BCS)	18.40	5.99	18.17	6.10	0.24	(0.728)
Share Workers (BCS)	34.12	7.33	33.98	8.71	0.14	(0.873)
Share Retirees (BCS)	2.36	1.67	2.23	1.52	0.13	(0.457)
Share Unemployed/Inactives (BCS)	17.84	8.28	17.23	8.06	0.61	(0.507)
Share Unknown or no Subject (BCS)	5.38	3.74	5.50	4.51	-0.11	(0.810)
Observations	158		164		322	

Table A4: Balance of Treatment Assignment (Individual Level)

	Randomization 2022		Randomization 2023	
	Coefficient	p-value	Coefficient	p-value
Sex	-0.037	0.157	0.037	0.263
Other Occupations	-0.068	0.100	0.028	0.601
Construction	0.053	0.354	-0.041	0.558
Electrotechnics and Energie	-0.012	0.810	-0.102*	0.078
Client Services	0.005	0.888	0.014	0.767
Hotel and Restaurations	0.018	0.817	0.090	0.261
Administrative Services	0.043	0.322	0.068	0.148
Woodwork and Furniture	-0.036	0.670	0.086	0.395
Logistics, Transport and Maintenance	0.044	0.429	-0.037	0.660
Industrial Maintenance	-0.025	0.795	0.012	0.904
Fashion, Clothing and Leather	-0.071	0.441	-0.031	0.704

NOTE: This table shows the coefficients from 11 separate OLS regressions testing whether a characteristic predicts treatment status. Standard errors are clustered at the strata level.

Table B1: Survey Response Attrition (schools)

	Randomization 2022		Randomization 2023	
	Coefficient	p-value	Coefficient	p-value
Treatment Assigned	0.022	0.664	0.040	0.476
Treatment Executed Once	-0.119	0.212	0.059	0.303
Treatment Executed Twice	0.176***	0.001		
Share Other Occupations	0.000	0.907	-0.000	0.675
Share Construction	-0.001	0.527	0.000	0.850
Share Electrotechnics and Energie	0.001	0.256	-0.002**	0.044
Share Client Services	0.000	0.794	0.001	0.427
Share Hotel and Restaurations	-0.001	0.583	0.000	0.894
Share Administrative Services	0.000	0.967	-0.001	0.457
Share Woodwork and Furniture	0.002	0.367	0.005*	0.096
Share Logistics, Transport and Maintenance	-0.001	0.382	0.002	0.187
Share Industrial Maintenance	-0.003	0.145	0.004	0.415
Share Fashion, Clothing and Leather	-0.001	0.871	0.000	0.957
Share Continuing Studies After Graduation (19/20)	0.000	0.907	-0.007**	0.046
Share Continuing Studies After Graduation (20/21)	-0.001	0.703	-0.006	0.107
Share Continuing Studies After Graduation (21/22)	-0.002	0.481	-0.006*	0.070
Share Employed 6 Months After Graduation (19/20)	-0.000	0.902	-0.001	0.669
Share Employed 6 Months After Graduation (20/21)	0.002	0.557	-0.000	0.969
Share Employed 6 Months After Graduation (21/22)	0.001	0.650	0.000	0.874
Value Added 6 Months After Graduation (19/20)	-0.002	0.633	-0.005	0.371
Value Added 6 Months After Graduation (20/21)	0.005	0.298	-0.004	0.413
Value Added 6 Months After Graduation (21/22)	0.002	0.717	-0.003	0.639
Share Employed 12 Months After Graduation (19/20)	-0.001	0.718	0.003	0.259
Share Employed 12 Months After Graduation (20/21)	0.001	0.752	0.001	0.625
Share Employed 18 Months After Graduation (19/20)	0.003	0.299	-0.000	0.936
Share Employed 24 Months After Graduation (19/20)	-0.000	0.933	0.001	0.641
Local Unemployment	-0.001	0.979	0.025	0.127
Median Local Living Standard (Euro)	-0.000*	0.070	-0.000***	0.007
Top to Bottom Decile Living Standard Ratio	-0.065	0.135	-0.161***	0.000

NOTE: This table shows the coefficients from separate OLS regressions testing whether a characteristic predicts a schools participation in the survey. The standard errors used for the p-values are robust and clustered at the strata level.

Table B2: Survey Response Attrition (students in responding schools)

	Randomization 2022		Randomization 2023	
	Coefficient	p-value	Coefficient	p-value
Treatment Assigned	-0.002	0.959	0.123***	0.005
Treatment Executed Once	-0.057	0.579	0.089**	0.031
Treatment Executed Twice	-0.007	0.852		
Sex	0.051**	0.023	-0.007	0.794
Other Occupations	0.026	0.537	-0.015	0.676
Construction	-0.074*	0.089	0.018	0.720
Electrotechnics and Energie	0.000	0.995	0.004	0.914
Client Services	0.025	0.426	-0.092***	0.009
Hotel and Restaurations	0.023	0.579	0.131***	0.009
Administrative Services	0.053	0.287	0.017	0.722
Woodwork and Furniture	-0.113*	0.067	0.100*	0.095
Logistics, Transport and Maintenance	-0.045	0.365	-0.022	0.635
Industrial Maintenance	-0.112	0.147	-0.020	0.818
Fashion, Clothing and Leather	0.019	0.819	0.048	0.365

NOTE: This table shows the coefficients from separate OLS regressions testing whether a characteristic predicts a student's participation in the survey. The standard errors used for the p-values are robust and clustered at the strata level.

Table B3: Survey Response Attrition (students in all schools)

	Randomization 2022		Randomization 2023	
	Coefficient	p-value	Coefficient	p-value
Treatment Assigned	0.028	0.342	0.066**	0.028
Treatment Executed Once	-0.081	0.137	0.050	0.123
Treatment Executed Twice	0.092***	0.004		
Sex	0.035**	0.047	0.017	0.319
Other Occupations	0.026	0.337	-0.002	0.950
Construction	-0.059*	0.056	0.018	0.613
Electrotechnics and Energie	0.016	0.573	-0.043*	0.070
Client Services	0.020	0.381	-0.030	0.194
Hotel and Restaurations	0.002	0.946	0.054	0.218
Administrative Services	0.023	0.458	-0.006	0.834
Woodwork and Furniture	-0.051	0.232	0.131**	0.024
Logistics, Transport and Maintenance	-0.045	0.171	0.019	0.629
Industrial Maintenance	-0.052	0.265	0.013	0.814
Fashion, Clothing and Leather	-0.020	0.710	0.015	0.729

NOTE: This table shows the coefficients from separate OLS regressions testing whether a characteristic predicts a student's participation in the survey. The standard errors used for the p-values are robust and clustered at the strata level.

Table B4: Predicting Student Response: Interaction of Treatment Assignment and Individual Characteristics

	(1) Within School 2022	(2) Overall 2022	(3) Within School 2023	(4) Overall 2023
Yes × Female	0.0327	0.0250	-0.00895	0.00675
	(1.39)	(1.47)	(-0.28)	(0.37)
Yes × Construction=1	-0.194*	-0.151*	-0.126	-0.0458
	(-1.86)	(-1.92)	(-1.10)	(-0.52)
Yes × Electrotechnics and Energie=1	-0.0257	-0.0462	0.122	-0.0221
	(-0.27)	(-0.68)	(1.27)	(-0.33)
Yes × Client Services=1	-0.0759	-0.0486	0.120	0.0107
	(-0.96)	(-0.82)	(1.35)	(0.17)
Yes × Hotel and Restaurations=1	-0.0298	-0.0398	0.191	0.0821
	(-0.28)	(-0.48)	(1.43)	(0.88)
Yes × Administrative Services=1	-0.0212	-0.00913	0.308***	0.120
	(-0.20)	(-0.12)	(2.85)	(1.62)
Yes × Woodwork and Furniture=1	-0.182	-0.124	0.0838	0.0551
	(-1.36)	(-1.33)	(0.63)	(0.43)
Yes × Logistics, Transport and Maintenance=1	-0.00938	-0.124	0.0739	0.0659
	(-0.08)	(-1.48)	(0.65)	(0.78)
Yes × Industrial Maintenance=1	-0.109	-0.0309	0.0151	-0.0655
	(-0.65)	(-0.32)	(0.09)	(-0.64)
Yes × Fashion, Clothing and Leather=1	-0.165	-0.0931	0.172	0.0353
	(-0.91)	(-0.86)	(1.58)	(0.38)
Observations	24886	49085	18160	40530
Joint F-test	Prob $\geq F = .552$	Prob $\geq F = .577$	Prob $\geq F = .053$	Prob $\geq F = .682$

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

NOTE: This table shows results of a regression of student response on individual characteristics interacted with treatment assignment. Column (1) reports results for students within schools randomized in 2022 that responded to the survey. Column (2) reports results for students within schools randomized in 2022 overall. Column (3) reports results for students within schools randomized in 2023 that responded to the survey. Column (4) reports results for students within schools randomized in 2023 overall. The results of an F-test testing whether the interaction coefficients are jointly zero is reported in the bottom. Standard errors are clustered at the strata level.

Table B5: Balance of Treatment Assignment among Schools Responding to Survey (Randomized in 2022)

	Control Assignment		Treatment Assignment		Difference	
	Mean	SD	Mean	SD	Difference	p-value
Survey Response Information						
Total Number of Responding Me	37.56	27.71	42.40	25.48	-4.84	(0.371)
Total Number of Responding Women	28.06	28.72	34.88	28.20	-6.82	(0.239)
Responding Men to Women Ratio	5.78	10.77	3.69	6.02	2.09	(0.253)
Student Field of Study: 2023/2024 (DEPP 2024)						
Share Other Occupations	15.65	24.09	15.71	22.08	-0.06	(0.986)
Share Construction	8.02	17.98	8.24	15.68	-0.22	(0.926)
Share Electrotechnics and Energie	22.06	29.65	23.65	28.38	-1.59	(0.698)
Share Client Services	20.31	26.01	21.84	25.57	-1.53	(0.674)
Share Hotel and Restaurations	9.02	20.61	9.15	21.09	-0.13	(0.965)
Share Administrative Services	8.19	15.90	9.01	15.59	-0.82	(0.713)
Share Woodwork and Furniture	4.04	15.60	2.75	7.57	1.29	(0.452)
Share Logistics, Transport and Maintenance	8.63	16.95	5.92	14.59	2.71	(0.225)
Share Industrial Maintenance	1.48	5.19	2.38	6.59	-0.90	(0.283)
Share Fashion, Clothing and Leather	2.60	8.77	1.35	4.59	1.25	(0.203)
School Performance (INSERJEUNE 2022)						
Share Continuing Studies After Graduation (19/20)	46.25	7.07	47.93	7.01	-1.68	(0.092)
Share Continuing Studies After Graduation (20/21)	48.25	7.24	49.15	7.11	-0.90	(0.372)
Share Continuing Studies After Graduation (21/22)	49.07	7.04	50.44	6.76	-1.37	(0.159)
Share Employed 6 Months After Graduation (19/20)	37.09	10.90	37.90	10.15	-0.81	(0.584)
Share Employed 6 Months After Graduation (20/21)	38.05	11.23	39.63	10.26	-1.58	(0.297)
Share Employed 6 Months After Graduation (21/22)	44.32	10.88	46.16	9.23	-1.85	(0.194)
Value Added 6 Months After Graduation (19/20)	-0.41	5.83	-0.91	4.83	0.49	(0.511)
Value Added 6 Months After Graduation (20/21)	0.33	6.00	0.34	4.84	-0.01	(0.993)
Value Added 6 Months After Graduation (21/22)	0.20	5.76	0.66	4.91	-0.46	(0.540)
Share Employed 12 Months After Graduation (19/20)	45.02	11.88	46.45	10.39	-1.43	(0.363)
Share Employed 12 Months After Graduation (20/21)	49.16	11.59	50.43	9.90	-1.27	(0.403)
Share Employed 18 Months After Graduation (19/20)	48.61	10.36	50.53	8.67	-1.92	(0.153)
Share Employed 24 Months After Graduation (19/20)	54.87	10.64	57.31	9.18	-2.44	(0.082)
Local Unemployment	6.98	1.48	6.84	1.39	0.14	(0.484)
Median Local Living Standard (Euro)	22389.71	1776.69	22273.78	1309.68	115.94	(0.597)
Top to Bottom Decile Living Standard Ratio	3.20	0.58	3.12	0.46	0.08	(0.293)
Summary: 2022/2023 (BCS 2022)						
Number of Students (BCS)	99.20	51.63	113.10	50.27	-13.90	(0.054)
Number of Male Students (BCS)	58.26	37.85	66.31	35.62	-8.05	(0.121)
Number of Female Students (BCS)	40.94	39.16	46.80	39.73	-5.85	(0.293)
Share of Male Students (BCS)	60.82	26.88	61.76	24.88	-0.93	(0.798)
Share of Female Students (BCS)	39.18	26.88	38.24	24.88	0.93	(0.798)
Men to Women Ratio (BCS)	6.16	13.59	6.84	13.81	-0.68	(0.731)
Average Age of Students (BCS)	17.35	0.20	17.35	0.15	-0.00	(0.973)
Nationalities: 2022/2023 (BCS 2022)						
Share French Nationality (BCS)	87.61	8.86	86.83	9.39	0.78	(0.547)
Share European (EU) Nationality (BCS)	2.84	2.70	2.91	3.17	-0.08	(0.850)
Share European (outside EU) Nationality (BCS)	1.48	1.92	1.88	2.45	-0.41	(0.193)
Share Asian Nationality (BCS)	2.31	2.45	2.27	2.69	0.04	(0.910)
Share African Nationality (BCS)	5.54	5.45	5.80	5.10	-0.27	(0.720)
Share American Nationality (BCS)	0.22	0.45	0.28	0.58	-0.07	(0.353)
Share Oceanic Nationality (BCS)	0.00	0.00	0.00	0.00	0.00	(.)
Share Nationality not defined (BCS)	0.01	0.10	0.01	0.11	0.00	(0.813)
Parents PCS: 2022/2023 (BCS 2022)						
Share Agriculture (BCS)	1.08	1.75	0.89	1.26	0.19	(0.382)
Share Artisans, Merchants, and Entrepreneurs (BCS)	7.15	3.74	8.22	3.55	-1.07	(0.039)
Share Executive Employees (Cadre) (BCS)	5.48	4.14	6.28	4.56	-0.80	(0.193)
Share Intermediary Professions (BCS)	9.45	4.08	9.87	4.23	-0.43	(0.465)
Share Employees (BCS)	16.07	5.92	16.31	5.92	-0.24	(0.774)
Share Workers (BCS)	37.09	9.81	34.81	8.01	2.28	(0.071)
Share Retirees (BCS)	2.09	2.44	1.90	1.70	0.20	(0.507)
Share Unemployed/Inactives (BCS)	16.10	7.84	16.06	7.94	0.04	(0.975)
Share Unknown or no Subject (BCS)	5.49	5.10	5.65	5.01	-0.16	(0.819)
Observations	104		98		202	

Table B6: Balance of Treatment Assignment among Schools Responding to Survey (Randomized in 2023)

	Control Assignment		Treatment Assignment		Difference	
	Mean	SD	Mean	SD	Difference	p-value
Survey Response Information						
Total Number of Responding Me	43.73	33.43	42.05	27.88	1.68	(0.832)
Total Number of Responding Women	19.73	14.45	31.73	28.29	-12.00	(0.026)
Responding Men to Women Ratio	5.46	10.86	6.42	11.34	-0.96	(0.738)
Student Field of Study: 2023/2024 (DEPP 2024)						
Share Other Occupations	15.09	21.66	18.63	26.16	-3.54	(0.381)
Share Construction	8.91	16.50	9.30	19.55	-0.40	(0.896)
Share Electrotechnics and Energie	20.01	27.25	11.52	22.11	8.49	(0.046)
Share Client Services	21.53	25.38	20.34	25.53	1.20	(0.781)
Share Hotel and Restaurations	8.41	20.35	13.11	24.51	-4.69	(0.217)
Share Administrative Services	6.76	11.98	8.76	16.61	-2.00	(0.409)
Share Woodwork and Furniture	4.01	11.13	5.39	14.93	-1.38	(0.532)
Share Logistics, Transport and Maintenance	8.97	20.41	7.84	20.34	1.13	(0.742)
Share Industrial Maintenance	2.15	7.28	1.84	5.69	0.31	(0.778)
Share Fashion, Clothing and Leather	4.15	9.22	3.27	9.80	0.88	(0.585)
School Performance (INSERJEUNE 2022)						
Share Continuing Studies After Graduation (19/20)	49.86	7.47	48.24	8.13	1.62	(0.219)
Share Continuing Studies After Graduation (20/21)	50.33	7.21	49.28	8.28	1.05	(0.421)
Share Continuing Studies After Graduation (21/22)	50.56	8.07	49.65	8.23	0.91	(0.510)
Share Employed 6 Months After Graduation (19/20)	32.65	11.09	33.31	11.42	-0.66	(0.731)
Share Employed 6 Months After Graduation (20/21)	33.97	11.18	34.25	10.77	-0.28	(0.879)
Share Employed 6 Months After Graduation (21/22)	41.36	9.97	42.72	10.55	-1.36	(0.434)
Value Added 6 Months After Graduation (19/20)	-1.80	5.04	-1.85	5.40	0.05	(0.954)
Value Added 6 Months After Graduation (20/21)	-0.89	5.12	-1.25	5.30	0.36	(0.683)
Value Added 6 Months After Graduation (21/22)	-0.09	4.48	0.35	5.14	-0.44	(0.590)
Share Employed 12 Months After Graduation (19/20)	40.65	11.09	43.57	11.37	-2.92	(0.125)
Share Employed 12 Months After Graduation (20/21)	44.38	11.28	46.76	11.61	-2.38	(0.219)
Share Employed 18 Months After Graduation (19/20)	45.53	10.17	45.96	10.60	-0.43	(0.806)
Share Employed 24 Months After Graduation (19/20)	52.36	10.46	53.67	10.24	-1.30	(0.457)
Local Unemployment	7.73	1.94	7.56	1.93	0.17	(0.604)
Median Local Living Standard (Euro)	22103.79	2368.52	22310.67	2655.86	-206.88	(0.626)
Top to Bottom Decile Living Standard Ratio	3.21	0.59	3.21	0.65	0.00	(0.969)
Summary: 2022/2023 (BCS 2022)						
Number of Students (BCS)	118.74	57.92	113.55	52.68	5.20	(0.580)
Number of Male Students (BCS)	70.77	44.00	59.61	38.32	11.16	(0.113)
Number of Female Students (BCS)	47.97	39.46	53.93	46.25	-5.96	(0.410)
Share of Male Students (BCS)	60.72	25.24	54.81	28.99	5.91	(0.198)
Share of Female Students (BCS)	39.28	25.24	45.19	28.99	-5.91	(0.198)
Men to Women Ratio (BCS)	8.27	20.29	5.96	13.28	2.31	(0.434)
Average Age of Students (BCS)	17.37	0.20	17.33	0.25	0.03	(0.366)
Nationalities: 2022/2023 (BCS 2022)						
Share French Nationality (BCS)	86.77	9.32	88.05	8.51	-1.28	(0.398)
Share European (EU) Nationality (BCS)	2.94	3.55	2.79	3.53	0.16	(0.794)
Share European (outside EU) Nationality (BCS)	1.00	1.40	1.34	1.96	-0.34	(0.239)
Share Asian Nationality (BCS)	1.79	1.81	1.97	2.26	-0.18	(0.594)
Share African Nationality (BCS)	7.02	6.98	5.51	4.95	1.51	(0.147)
Share American Nationality (BCS)	0.49	0.89	0.34	0.71	0.15	(0.267)
Share Oceanic Nationality (BCS)	0.00	0.00	0.00	0.00	0.00	(.)
Share Nationality not defined (BCS)	0.00	0.00	0.01	0.12	-0.01	(0.321)
Parents PCS: 2022/2023 (BCS 2022)						
Share Agriculture (BCS)	1.06	2.14	0.69	1.27	0.36	(0.235)
Share Artisans, Merchants, and Entrepreneurs (BCS)	7.33	3.59	7.24	4.06	0.09	(0.894)
Share Executive Employees (Cadre) (BCS)	5.37	4.31	5.67	5.96	-0.30	(0.734)
Share Intermediary Professions (BCS)	8.74	4.19	9.30	3.67	-0.57	(0.397)
Share Employees (BCS)	18.33	6.02	16.29	4.76	2.03	(0.029)
Share Workers (BCS)	33.58	8.20	34.79	9.11	-1.21	(0.409)
Share Retirees (BCS)	2.19	1.62	2.17	1.45	0.02	(0.948)
Share Unemployed/Inactives (BCS)	18.47	9.67	18.20	8.25	0.27	(0.860)
Share Unknown or no Subject (BCS)	4.94	3.53	5.64	4.13	-0.70	(0.282)
Observations	66		75		141	

Table B7: Balance of Treatment Assignment among Survey Respondents (Individual Level)

	Randomization 2022		Randomization 2023	
	Coefficient	p-value	Coefficient	p-value
Sex	0.013	0.761	0.060	0.247
Other Occupations	0.011	0.863	-0.014	0.868
Construction	-0.053	0.548	-0.152	0.145
Electrotechnics and Energie	0.007	0.923	-0.145	0.103
Client Services	0.007	0.906	0.006	0.936
Hotel and Restaurations	0.020	0.859	0.142	0.151
Administrative Services	0.086	0.231	0.213***	0.004
Woodwork and Furniture	-0.125	0.353	-0.007	0.956
Logistics, Transport and Maintenance	-0.070	0.477	0.059	0.591
Industrial Maintenance	0.012	0.926	-0.118	0.345
Fashion, Clothing and Leather	-0.103	0.437	-0.005	0.969

NOTE: This table shows the coefficients from separate OLS regressions testing whether a characteristic predicts treatment status. Standard errors were clustered at the strata level.

Table B8: Balance of Treatment Assignment among Schools Not Responding to Survey (Randomized in 2022)

	Control Assignment		Treatment Assignment		Difference	
	Mean	SD	Mean	SD	Difference	p-value
Survey Response Information						
Number of Respondents Expected	131.01	69.86	126.10	66.73	4.91	(0.623)
Men to Women Ratio	5.84	12.75	9.40	18.78	-3.56	(0.144)
Student Field of Study: 2023/2024 (DEPP 2024)						
Share Other Occupations	15.66	24.95	15.07	25.26	0.60	(0.871)
Share Construction	7.44	16.96	11.46	19.26	-4.02	(0.134)
Share Electrotechnics and Energie	19.90	27.67	18.86	24.70	1.04	(0.786)
Share Client Services	22.73	26.70	17.65	23.85	5.08	(0.170)
Share Hotel and Restaurations	11.14	23.58	9.29	19.99	1.85	(0.561)
Share Administrative Services	8.66	15.08	8.35	18.01	0.32	(0.897)
Share Woodwork and Furniture	2.63	8.02	2.57	7.89	0.06	(0.958)
Share Logistics, Transport and Maintenance	6.85	16.86	11.37	24.33	-4.52	(0.147)
Share Industrial Maintenance	2.72	8.29	3.41	15.50	-0.69	(0.712)
Share Fashion, Clothing and Leather	2.24	5.55	1.97	8.96	0.28	(0.803)
School Performance (INSERJEUNE 2022)						
Share Continuing Studies After Graduation (19/20)	47.20	7.29	46.71	8.52	0.49	(0.678)
Share Continuing Studies After Graduation (20/21)	49.58	7.36	48.26	7.74	1.32	(0.235)
Share Continuing Studies After Graduation (21/22)	50.99	7.77	49.36	7.04	1.63	(0.132)
Share Employed 6 Months After Graduation (19/20)	37.68	11.57	37.57	11.02	0.11	(0.948)
Share Employed 6 Months After Graduation (20/21)	37.78	11.54	38.34	11.79	-0.56	(0.742)
Share Employed 6 Months After Graduation (21/22)	44.53	11.25	44.84	10.60	-0.30	(0.849)
Value Added 6 Months After Graduation (19/20)	0.29	5.44	-1.15	4.90	1.44	(0.058)
Value Added 6 Months After Graduation (20/21)	0.10	4.85	-0.72	5.49	0.82	(0.281)
Value Added 6 Months After Graduation (21/22)	0.24	5.02	0.23	5.33	0.01	(0.992)
Share Employed 12 Months After Graduation (19/20)	46.19	12.62	46.21	11.87	-0.02	(0.992)
Share Employed 12 Months After Graduation (20/21)	48.97	11.88	49.79	12.29	-0.82	(0.643)
Share Employed 18 Months After Graduation (19/20)	48.12	10.73	48.57	10.08	-0.46	(0.764)
Share Employed 24 Months After Graduation (19/20)	56.34	10.49	55.92	10.37	0.42	(0.785)
Local Unemployment	6.83	1.18	7.02	1.41	-0.20	(0.315)
Median Local Living Standard (Euro)	22605.80	1908.34	22732.71	2208.55	-126.91	(0.679)
Top to Bottom Decile Living Standard Ratio	3.20	0.56	3.29	0.63	-0.10	(0.281)
Summary: 2022/2023 (BCS 2022)						
Number of Students (BCS)	115.82	55.70	109.40	49.73	6.43	(0.406)
Number of Male Students (BCS)	66.21	37.39	70.47	40.43	-4.26	(0.459)
Number of Female Students (BCS)	49.61	46.74	38.93	34.25	10.68	(0.074)
Share of Male Students (BCS)	60.85	24.52	66.06	24.58	-5.21	(0.150)
Share of Female Students (BCS)	39.15	24.52	33.94	24.58	5.21	(0.150)
Men to Women Ratio (BCS)	7.94	18.39	6.25	11.08	1.70	(0.445)
Average Age of Students (BCS)	17.38	0.19	17.40	0.18	-0.02	(0.485)
Nationalities: 2022/2023 (BCS 2022)						
Share French Nationality (BCS)	85.85	10.37	85.82	9.14	0.02	(0.988)
Share European (EU) Nationality (BCS)	3.06	3.60	2.98	2.95	0.08	(0.868)
Share European (outside EU) Nationality (BCS)	1.47	1.93	1.28	2.23	0.19	(0.544)
Share Asian Nationality (BCS)	2.33	2.50	2.26	2.99	0.07	(0.864)
Share African Nationality (BCS)	6.90	7.59	7.23	6.54	-0.33	(0.751)
Share American Nationality (BCS)	0.39	0.81	0.36	0.81	0.03	(0.819)
Share Oceanic Nationality (BCS)	0.01	0.07	0.01	0.09	-0.00	(0.799)
Share Nationality not defined (BCS)	0.00	0.00	0.06	0.24	-0.06	(0.033)
Parents PCS: 2022/2023 (BCS 2022)						
Share Agriculture (BCS)	0.66	0.95	0.71	1.34	-0.05	(0.771)
Share Artisans, Merchants, and Entrepreneurs (BCS)	7.79	4.24	7.62	3.75	0.17	(0.770)
Share Executive Employees (Cadre) (BCS)	5.96	3.58	6.20	4.75	-0.24	(0.700)
Share Intermediary Professions (BCS)	9.82	4.29	10.08	4.40	-0.27	(0.676)
Share Employees (BCS)	17.81	6.74	17.71	6.37	0.10	(0.916)
Share Workers (BCS)	34.89	9.66	33.82	8.90	1.07	(0.432)
Share Retirees (BCS)	1.65	1.48	1.86	1.66	-0.21	(0.363)
Share Unemployed/Inactives (BCS)	16.14	8.18	16.26	8.38	-0.11	(0.927)
Share Unknown or no Subject (BCS)	5.28	5.12	5.74	6.11	-0.46	(0.580)
Observations	101		87		188	

Table B9: Balance of Treatment Assignment among Schools Not Responding to Survey (Randomized in 2023)

	Control Assignment		Treatment Assignment		Difference	
	Mean	SD	Mean	SD	Difference	p-value
Survey Response Information						
Number of Respondents Expected	122.82	59.21	124.42	57.14	-1.60	(0.853)
Men to Women Ratio	8.46	18.17	8.45	21.80	0.01	(0.998)
Student Field of Study: 2023/2024 (DEPP 2024)						
Share Other Occupations	17.90	27.36	18.29	29.33	-0.40	(0.925)
Share Construction	9.44	18.24	8.07	15.70	1.37	(0.589)
Share Electrotechnics and Energie	23.30	30.37	19.63	28.18	3.66	(0.401)
Share Client Services	18.10	27.98	18.97	26.51	-0.87	(0.831)
Share Hotel and Restaurations	8.94	21.33	12.22	25.93	-3.29	(0.354)
Share Administrative Services	8.33	15.11	9.98	20.16	-1.65	(0.536)
Share Woodwork and Furniture	2.63	11.31	2.24	6.53	0.39	(0.775)
Share Logistics, Transport and Maintenance	5.96	15.36	5.80	15.90	0.16	(0.945)
Share Industrial Maintenance	1.17	3.21	1.81	6.11	-0.64	(0.383)
Share Fashion, Clothing and Leather	4.24	13.71	2.98	7.50	1.25	(0.445)
School Performance (INSERJEUNE 2022)						
Share Continuing Studies After Graduation (19/20)	51.61	7.30	49.76	6.96	1.84	(0.084)
Share Continuing Studies After Graduation (20/21)	52.04	7.31	50.38	7.47	1.66	(0.132)
Share Continuing Studies After Graduation (21/22)	52.12	8.10	51.19	7.35	0.93	(0.422)
Share Employed 6 Months After Graduation (19/20)	34.36	11.69	32.66	10.06	1.70	(0.296)
Share Employed 6 Months After Graduation (20/21)	34.98	11.21	33.33	9.51	1.65	(0.286)
Share Employed 6 Months After Graduation (21/22)	42.62	10.88	41.15	9.66	1.47	(0.338)
Value Added 6 Months After Graduation (19/20)	-0.71	5.51	-1.90	5.25	1.19	(0.138)
Value Added 6 Months After Graduation (20/21)	-0.05	5.46	-1.21	4.94	1.16	(0.136)
Value Added 6 Months After Graduation (21/22)	0.96	5.29	-0.17	4.83	1.13	(0.137)
Share Employed 12 Months After Graduation (19/20)	41.25	12.31	40.25	11.10	1.00	(0.565)
Share Employed 12 Months After Graduation (20/21)	45.62	11.75	44.43	10.60	1.19	(0.474)
Share Employed 18 Months After Graduation (19/20)	46.45	10.48	45.24	9.76	1.21	(0.422)
Share Employed 24 Months After Graduation (19/20)	52.92	9.65	52.11	9.44	0.81	(0.568)
Local Unemployment	7.34	1.66	7.30	1.59	0.03	(0.890)
Median Local Living Standard (Euro)	23035.54	2499.30	23262.36	2522.05	-226.82	(0.544)
Top to Bottom Decile Living Standard Ratio	3.61	0.89	3.68	0.90	-0.07	(0.595)
Summary: 2022/2023 (BCS 2022)						
Number of Students (BCS)	111.14	52.03	117.52	52.59	-6.38	(0.416)
Number of Male Students (BCS)	69.21	42.60	69.69	39.44	-0.48	(0.937)
Number of Female Students (BCS)	41.93	35.50	47.83	37.40	-5.89	(0.282)
Share of Male Students (BCS)	62.06	27.43	60.47	25.34	1.59	(0.688)
Share of Female Students (BCS)	37.94	27.43	39.53	25.34	-1.59	(0.688)
Men to Women Ratio (BCS)	7.80	15.15	9.11	18.94	-1.31	(0.615)
Average Age of Students (BCS)	17.39	0.18	17.37	0.17	0.01	(0.598)
Nationalities: 2022/2023 (BCS 2022)						
Share French Nationality (BCS)	85.44	10.68	84.85	10.03	0.59	(0.705)
Share European (EU) Nationality (BCS)	2.63	2.29	3.36	3.26	-0.73	(0.088)
Share European (outside EU) Nationality (BCS)	0.98	1.31	0.94	1.26	0.05	(0.808)
Share Asian Nationality (BCS)	2.23	2.29	2.23	2.13	-0.00	(0.995)
Share African Nationality (BCS)	8.22	7.39	7.83	6.63	0.39	(0.709)
Share American Nationality (BCS)	0.51	0.86	0.77	1.13	-0.26	(0.082)
Share Oceanic Nationality (BCS)	0.00	0.00	0.01	0.07	-0.01	(0.320)
Share Nationality not defined (BCS)	0.00	0.00	0.03	0.21	-0.03	(0.232)
Parents PCS: 2022/2023 (BCS 2022)						
Share Agriculture (BCS)	0.61	1.19	0.77	1.38	-0.16	(0.394)
Share Artisans, Merchants, and Entrepreneurs (BCS)	6.90	4.23	7.15	3.70	-0.24	(0.682)
Share Executive Employees (Cadre) (BCS)	4.62	3.46	5.88	3.88	-1.26	(0.023)
Share Intermediary Professions (BCS)	9.33	3.98	9.09	3.60	0.24	(0.673)
Share Employees (BCS)	18.46	6.01	19.78	6.67	-1.33	(0.165)
Share Workers (BCS)	34.51	6.66	33.28	8.34	1.23	(0.278)
Share Retirees (BCS)	2.48	1.71	2.27	1.58	0.21	(0.398)
Share Unemployed/Inactives (BCS)	17.39	7.14	16.40	7.84	0.99	(0.380)
Share Unknown or no Subject (BCS)	5.70	3.87	5.37	4.84	0.33	(0.618)
Observations	92		89		181	

Table B10: Balance of Treatment Assignment in Complete Strata (Randomized in 2022)

	Control Assignment		Treatment Assignment		Difference	
	Mean	SD	Mean	SD	Difference	p-value
Survey Response Information						
Total Number of Responding Me	37.67	24.43	37.85	23.12	-0.18	(0.982)
Total Number of Responding Women	31.00	28.02	33.70	25.89	-2.70	(0.773)
Responding Men to Women Ratio	3.73	5.30	3.71	6.99	0.02	(0.994)
Student Field of Study: 2023/2024 (DEPP 2024)						
Share Other Occupations	19.68	27.66	16.42	21.97	3.26	(0.603)
Share Construction	7.38	17.84	7.79	14.26	-0.41	(0.919)
Share Electrotechnics and Energie	18.39	27.73	18.34	23.86	0.05	(0.994)
Share Client Services	23.03	29.13	26.67	25.42	-3.64	(0.595)
Share Hotel and Restaurations	13.06	28.03	9.04	21.68	4.02	(0.524)
Share Administrative Services	7.62	13.68	13.95	19.84	-6.33	(0.132)
Share Woodwork and Furniture	1.98	6.54	0.96	3.10	1.02	(0.437)
Share Logistics, Transport and Maintenance	5.84	14.03	4.38	9.21	1.45	(0.628)
Share Industrial Maintenance	1.02	3.93	1.07	3.11	-0.05	(0.959)
Share Fashion, Clothing and Leather	2.00	6.32	1.38	5.08	0.61	(0.670)
School Performance (INSERJEUNE 2022)						
Share Continuing Studies After Graduation (19/20)	47.17	8.13	47.11	7.65	0.06	(0.977)
Share Continuing Studies After Graduation (20/21)	48.77	7.99	48.97	7.99	-0.21	(0.917)
Share Continuing Studies After Graduation (21/22)	49.10	6.94	50.25	6.97	-1.15	(0.506)
Share Employed 6 Months After Graduation (19/20)	35.43	11.45	37.03	9.29	-1.59	(0.542)
Share Employed 6 Months After Graduation (20/21)	38.03	11.32	38.86	8.76	-0.83	(0.748)
Share Employed 6 Months After Graduation (21/22)	44.57	10.19	45.94	8.13	-1.38	(0.552)
Value Added 6 Months After Graduation (19/20)	-0.60	6.18	-1.22	4.80	0.62	(0.655)
Value Added 6 Months After Graduation (20/21)	0.72	5.92	-0.25	4.82	0.97	(0.477)
Value Added 6 Months After Graduation (21/22)	0.70	6.05	0.58	5.17	0.12	(0.934)
Share Employed 12 Months After Graduation (19/20)	44.43	13.01	46.47	9.87	-2.04	(0.484)
Share Employed 12 Months After Graduation (20/21)	49.59	13.31	49.97	9.32	-0.39	(0.895)
Share Employed 18 Months After Graduation (19/20)	47.60	10.60	49.69	7.09	-2.09	(0.360)
Share Employed 24 Months After Graduation (19/20)	55.60	11.05	56.14	8.77	-0.54	(0.830)
Local Unemployment	6.90	1.16	6.78	1.34	0.12	(0.695)
Median Local Living Standard (Euro)	22318.00	1081.74	22410.83	1337.49	-92.83	(0.756)
Top to Bottom Decile Living Standard Ratio	3.16	0.50	3.17	0.56	-0.02	(0.906)
Summary: 2022/2023 (BCS 2022)						
Number of Students (BCS)	101.00	56.96	108.97	41.36	-7.97	(0.526)
Number of Male Students (BCS)	56.13	38.90	60.86	35.67	-4.73	(0.612)
Number of Female Students (BCS)	44.87	36.80	48.11	33.88	-3.24	(0.713)
Share of Male Students (BCS)	55.38	26.46	56.49	25.93	-1.11	(0.865)
Share of Female Students (BCS)	44.62	26.46	43.51	25.93	1.11	(0.865)
Men to Women Ratio (BCS)	4.73	11.18	8.56	18.64	-3.83	(0.314)
Average Age of Students (BCS)	17.30	0.13	17.36	0.14	-0.06	(0.089)
Nationalities: 2022/2023 (BCS 2022)						
Share French Nationality (BCS)	89.07	8.07	85.47	9.21	3.60	(0.096)
Share European (EU) Nationality (BCS)	2.71	2.85	3.88	3.87	-1.17	(0.165)
Share European (outside EU) Nationality (BCS)	1.20	2.41	2.06	2.62	-0.86	(0.172)
Share Asian Nationality (BCS)	2.12	2.37	2.23	2.12	-0.11	(0.847)
Share African Nationality (BCS)	4.70	3.89	6.03	5.91	-1.33	(0.278)
Share American Nationality (BCS)	0.19	0.40	0.30	0.70	-0.11	(0.437)
Share Oceanic Nationality (BCS)	0.00	0.00	0.00	0.00	0.00	(.)
Share Nationality not defined (BCS)	0.00	0.00	0.03	0.18	-0.03	(0.324)
Parents PCS: 2022/2023 (BCS 2022)						
Share Agriculture (BCS)	1.46	2.36	0.99	1.46	0.47	(0.343)
Share Artisans, Merchants, and Entrepreneurs (BCS)	8.28	3.64	8.82	3.93	-0.54	(0.563)
Share Executive Employees (Cadre) (BCS)	5.75	3.80	5.95	4.17	-0.20	(0.838)
Share Intermediary Professions (BCS)	9.32	3.26	9.16	3.82	0.17	(0.849)
Share Employees (BCS)	15.20	5.72	15.72	5.64	-0.52	(0.715)
Share Workers (BCS)	36.79	8.19	34.68	7.61	2.11	(0.286)
Share Retirees (BCS)	2.03	1.61	1.88	1.87	0.15	(0.722)
Share Unemployed/Inactives (BCS)	16.20	7.09	17.04	7.66	-0.84	(0.645)
Share Unknown or no Subject (BCS)	4.97	4.68	5.78	4.66	-0.80	(0.489)
Observations	30		36		66	

Table B11: Balance of Treatment Assignment in Complete Strata (Randomized in 2023)

	Control Assignment		Treatment Assignment		Difference	
	Mean	SD	Mean	SD	Difference	p-value
Survey Response Information						
Total Number of Responding Me	50.33	34.29	31.33	15.12	19.00	(0.095)
Total Number of Responding Women	23.25	16.20	41.67	35.77	-18.42	(0.090)
Responding Men to Women Ratio	6.00	13.70	3.33	7.89	2.67	(0.571)
Student Field of Study: 2023/2024 (DEPP 2024)						
Share Other Occupations	15.90	23.96	24.25	30.07	-8.36	(0.231)
Share Construction	10.52	19.05	5.91	16.07	4.61	(0.307)
Share Electrotechnics and Energie	21.41	28.14	9.27	17.36	12.13	(0.046)
Share Client Services	19.09	23.78	23.16	27.52	-4.07	(0.536)
Share Hotel and Restaurations	13.06	26.83	14.26	20.90	-1.21	(0.844)
Share Administrative Services	4.59	10.07	9.07	14.81	-4.48	(0.170)
Share Woodwork and Furniture	3.33	9.56	4.45	11.53	-1.12	(0.679)
Share Logistics, Transport and Maintenance	6.79	19.86	5.15	19.18	1.64	(0.742)
Share Industrial Maintenance	1.36	4.12	2.10	5.14	-0.74	(0.532)
Share Fashion, Clothing and Leather	3.96	8.58	2.37	6.01	1.59	(0.403)
School Performance (INSERJEUNE 2022)						
Share Continuing Studies After Graduation (19/20)	51.23	8.42	48.42	8.20	2.81	(0.189)
Share Continuing Studies After Graduation (20/21)	50.16	7.32	49.52	8.44	0.65	(0.749)
Share Continuing Studies After Graduation (21/22)	49.48	8.99	49.55	8.24	-0.06	(0.977)
Share Employed 6 Months After Graduation (19/20)	30.55	11.94	29.55	10.65	1.00	(0.729)
Share Employed 6 Months After Graduation (20/21)	32.35	12.83	30.29	10.16	2.06	(0.485)
Share Employed 6 Months After Graduation (21/22)	39.00	11.85	39.45	10.34	-0.45	(0.874)
Value Added 6 Months After Graduation (19/20)	-2.42	5.12	-3.03	4.53	0.61	(0.620)
Value Added 6 Months After Graduation (20/21)	-1.55	5.97	-2.84	4.94	1.29	(0.358)
Value Added 6 Months After Graduation (21/22)	-1.10	4.74	-0.90	4.36	-0.19	(0.868)
Share Employed 12 Months After Graduation (19/20)	39.03	12.78	40.61	10.87	-1.58	(0.602)
Share Employed 12 Months After Graduation (20/21)	43.10	13.28	43.71	10.87	-0.61	(0.843)
Share Employed 18 Months After Graduation (19/20)	43.16	10.27	42.90	10.56	0.26	(0.923)
Share Employed 24 Months After Graduation (19/20)	50.45	11.61	51.23	10.49	-0.77	(0.784)
Local Unemployment	7.98	2.13	8.07	2.16	-0.09	(0.869)
Median Local Living Standard (Euro)	21880.97	2468.56	21964.84	2909.11	-83.87	(0.903)
Top to Bottom Decile Living Standard Ratio	3.18	0.63	3.25	0.75	-0.08	(0.661)
Summary: 2022/2023 (BCS 2022)						
Number of Students (BCS)	122.23	64.89	119.26	58.93	2.97	(0.851)
Number of Male Students (BCS)	74.16	54.03	55.13	36.58	19.03	(0.110)
Number of Female Students (BCS)	48.06	43.46	64.13	52.21	-16.06	(0.193)
Share of Male Students (BCS)	60.71	27.78	49.60	27.75	11.12	(0.120)
Share of Female Students (BCS)	39.29	27.78	50.40	27.75	-11.12	(0.120)
Men to Women Ratio (BCS)	11.15	27.05	5.55	14.34	5.60	(0.313)
Average Age of Students (BCS)	17.35	0.23	17.31	0.25	0.04	(0.538)
Nationalities: 2022/2023 (BCS 2022)						
Share French Nationality (BCS)	88.75	9.29	89.57	9.12	-0.82	(0.726)
Share European (EU) Nationality (BCS)	2.12	2.22	2.55	2.99	-0.43	(0.525)
Share European (outside EU) Nationality (BCS)	0.87	1.48	1.02	1.97	-0.15	(0.730)
Share Asian Nationality (BCS)	1.75	1.96	1.76	2.29	-0.01	(0.980)
Share African Nationality (BCS)	6.18	6.94	4.66	4.91	1.52	(0.324)
Share American Nationality (BCS)	0.33	0.85	0.43	0.78	-0.10	(0.638)
Share Oceanic Nationality (BCS)	0.00	0.00	0.00	0.00	0.00	(.)
Share Nationality not defined (BCS)	0.00	0.00	0.00	0.00	0.00	(.)
Parents PCS: 2022/2023 (BCS 2022)						
Share Agriculture (BCS)	1.20	2.91	0.66	1.11	0.55	(0.335)
Share Artisans, Merchants, and Entrepreneurs (BCS)	6.83	3.06	6.79	4.09	0.03	(0.971)
Share Executive Employees (Cadre) (BCS)	5.19	4.23	5.38	7.47	-0.19	(0.904)
Share Intermediary Professions (BCS)	8.92	4.98	8.55	3.06	0.36	(0.731)
Share Employees (BCS)	17.63	4.41	16.00	5.28	1.62	(0.194)
Share Workers (BCS)	34.13	7.76	36.56	9.09	-2.43	(0.262)
Share Retirees (BCS)	2.24	1.97	2.34	1.68	-0.09	(0.846)
Share Unemployed/Inactives (BCS)	19.19	11.05	18.58	8.89	0.61	(0.811)
Share Unknown or no Subject (BCS)	4.66	3.75	5.13	4.02	-0.47	(0.639)
Observations	31		31		62	

Table B12: Balance of Treatment Assignment among Survey Respondents in Complete Strata (Individual Level)

	Randomization 2022		Randomization 2023	
	Coefficient	p-value	Coefficient	p-value
Sex	-0.007	0.918	0.142*	0.066
Other Occupations	-0.073	0.469	0.094	0.542
Construction	0.197	0.166	-0.297*	0.056
Electrotechnics and Energie	-0.056	0.684	-0.307**	0.021
Client Services	0.035	0.729	0.069	0.564
Hotel and Restaurations	-0.036	0.890	0.116	0.423
Administrative Services	0.149	0.201	0.248**	0.045
Woodwork and Furniture	-0.165	0.108	-0.020	0.922
Logistics, Transport and Maintenance	-0.252	0.249	0.056	0.868
Industrial Maintenance	0.138	0.384	-0.171	0.286
Fashion, Clothing and Leather	-0.100	0.704	0.130	0.391

NOTE: This table shows the coefficients from separate OLS regressions testing whether a characteristic predicts treatment status. Columns (1) and (2) report results for the full sample, columns (3) and (4) for students that are at a school which's randomization was performed in 2022, and columns (5) and (6) for students that are at a school which's randomization was performed in 2023. The standard errors used for the p-values are robust and clustered at the strata level.

Figure B1: Density of Survey Completion Time

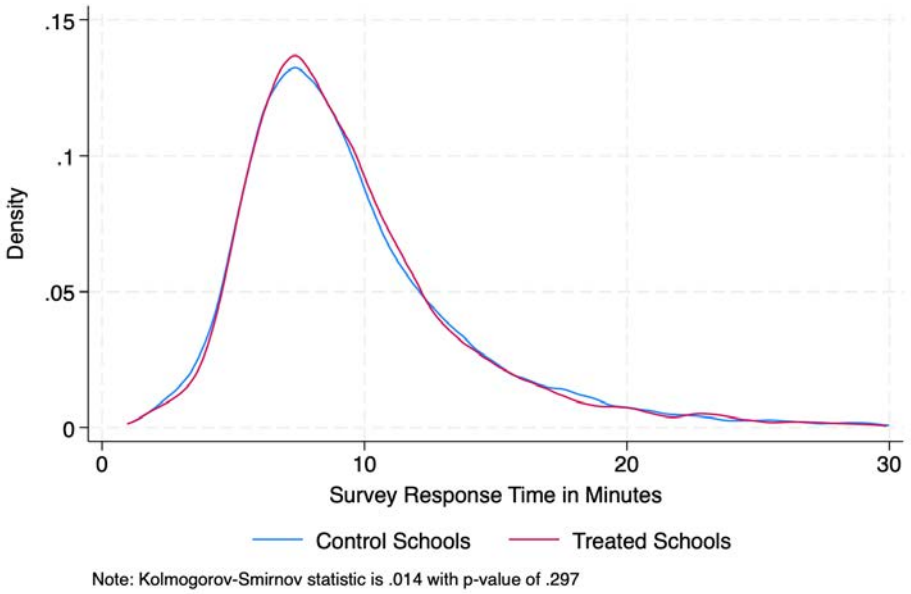


Table B13: Regression of Time Taken to Respond to Survey on Treatment Status

	Response Time 2022	Response Time 2023	5% Fastest Respondents 2022	5% fastest respondents 2023
Treatment Assigned	-0.0622	-0.0385	-0.0111*	-0.00274
	(-0.27)	(-0.14)	(-1.67)	(-0.38)
Constant	9.822***	9.852***	0.0557***	0.0515***
	(52.53)	(40.21)	(10.32)	(7.95)
Observations	10859	7976	10859	7976

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

NOTE: This table shows the coefficients from separate OLS regressions testing whether treatment assignment predicts time spent on the survey. Columns (1) and (2) report results for overall time taken. Columns (3) and (4) for an indicator equal to one if a responded is among the 5 fastest percent. In 2022, the 5 fastest percent responded to the survey in under 4.52 minutes. In 2023, the 5 fastest percent responded to the survey in under 4.49 minutes. The standard errors are robust and clustered at the strata level.

Figure B2: Subjective 6-Month vs. 12-Month Job-Find Probability

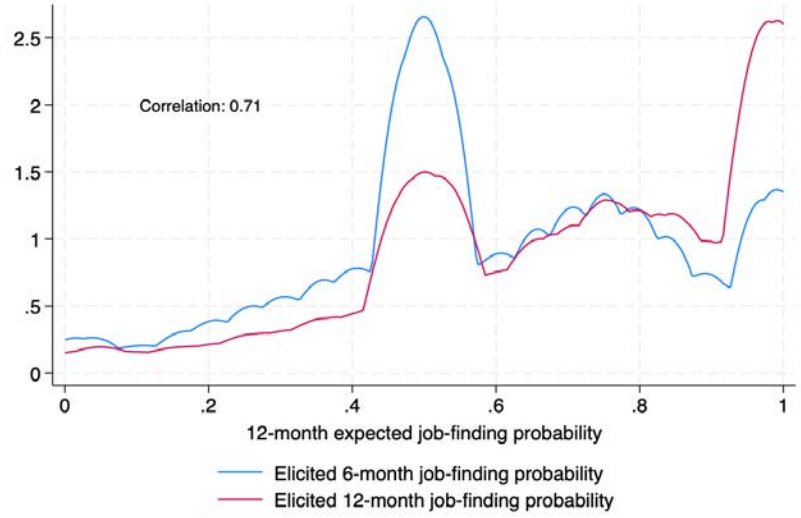


Figure B3: Subjective 6-Month vs. 12-Month Job-Find Probability (Cumulative Distribution)

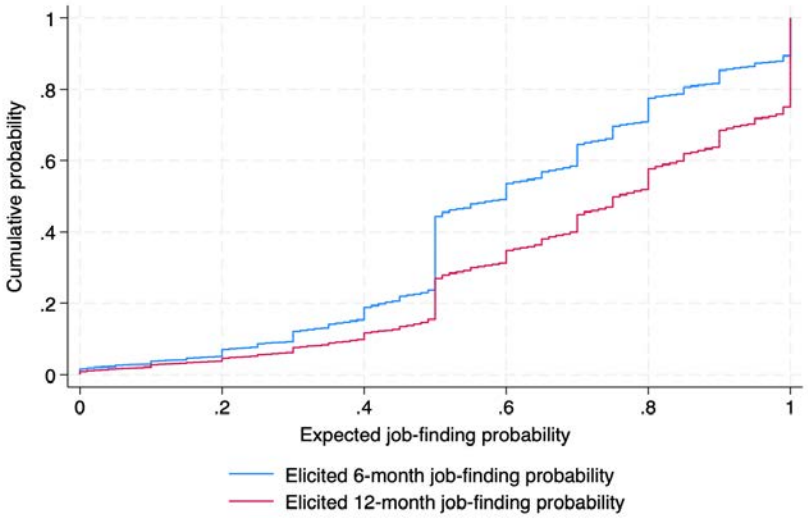
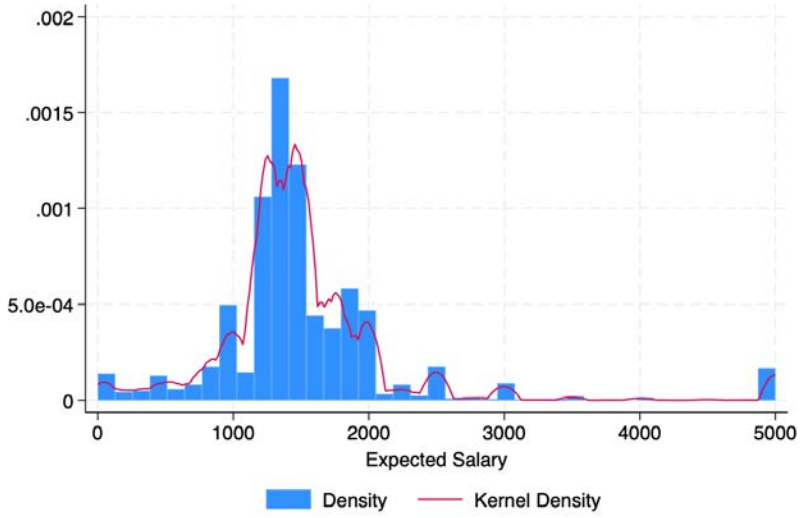
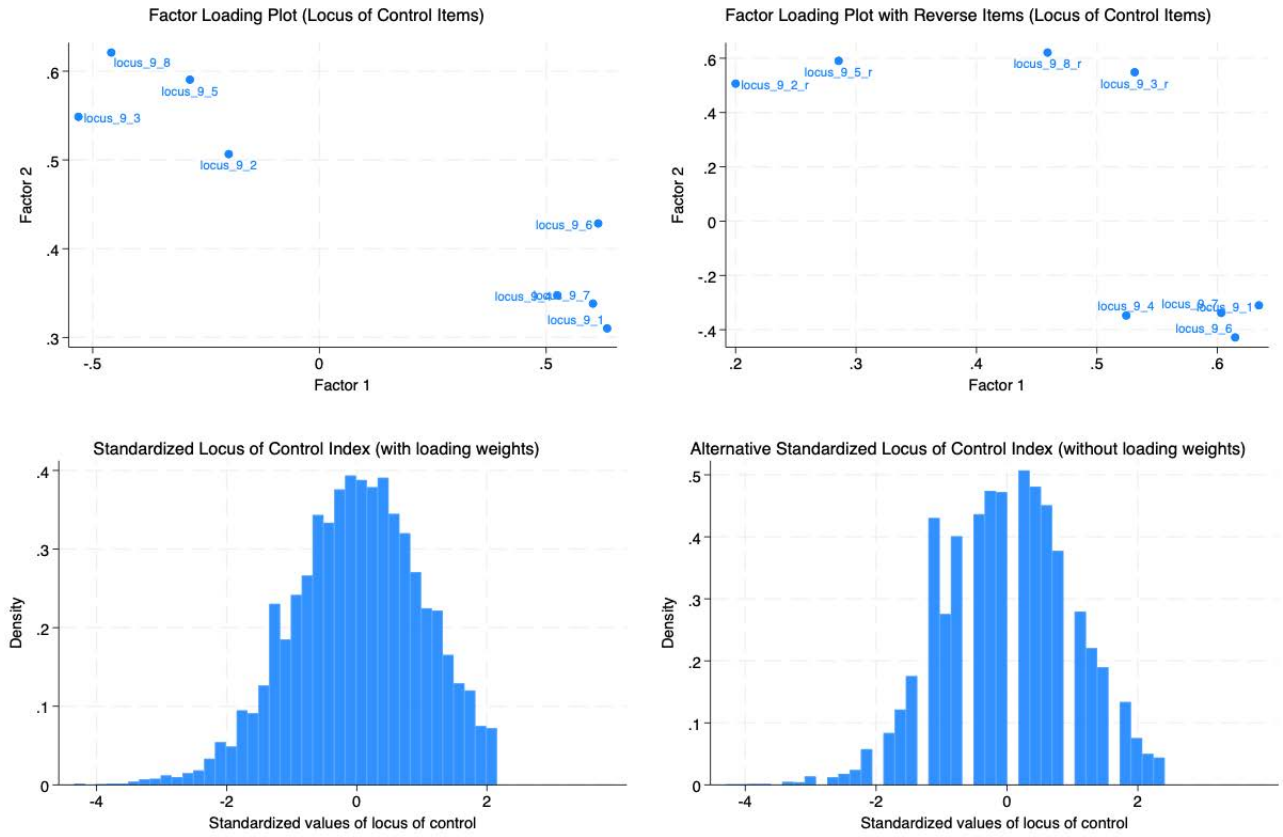


Figure B4: Distribution of Salary Expectations



Note: observations with expected net monthly salary above 5000 Euro get winsorized to 5000

Figure B5: Locus of Control: Factor Analysis and Distribution



Note: The upper left figure shows the factor loading of the 8 components of Locus of Control (LOC) questionaire. Four components clearly load on factor 2, characterized as external LOC, 4 components load more on factor 1, characterized as internal LOC. The upper right figure shows the factor loading of the 8 components of LOC with reverse coding for components loading on external LOC. All components now load on Factor 1. The lower left figure shows the distribution of the standardized LOC measure (increasing in internal LOC) using the loading weights from the principal component analysis including the reverse coded components. The lower right figures shows the distribution of the standardized LOCS measure (increasing in internal LOC) not using the loading weights as before.

Table C1: Regression Robustness Extraversion (standardized)

Dependent Variable: Extraversion (standardized)

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Panel A1: 2022 Sample						
Treatment Assigned	0.045***	0.048***	0.044***	0.057***	0.074***	0.055***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]			
Observations	10859	10859	10316	10859	10859	10316
Panel A2: 2023 Sample						
Treatment Assigned	0.020	0.015	0.015	0.030	-0.050	0.023
	(0.428)	(0.545)	(0.521)	(0.428)	(0.422)	(0.520)
	[0.548]	[0.651]	[0.652]			
Observations	7976	7976	7577	7976	7976	7577
Panel B1: 2022 without Grand-Est and Pays de la Loire						
Treatment Assigned	0.034**	0.038**	0.033**	0.037**	0.052**	0.036**
	(0.035)	(0.018)	(0.038)	(0.031)	(0.013)	(0.035)
	[0.038]	[0.011]	[0.051]			
Observations	5654	5654	5379	5654	5654	5379
Panel C1: 2022 Sample without Incomplete Strata						
Treatment Assigned	0.050***	0.049***	0.043***	0.063***	0.049***	0.055***
	(0.001)	(0.002)	(0.003)	(0.001)	(0.006)	(0.004)
	[0.015]	[0.009]	[0.033]			
Observations	3793	3793	3600	3793	3793	3600
Panel C2: 2023 Sample without Incomplete Strata						
Treatment Assigned	-0.004	-0.019	-0.008	-0.006	-0.071	-0.011
	(0.913)	(0.645)	(0.837)	(0.911)	(0.277)	(0.834)
	[0.924]	[0.692]	[0.451]			
Observations	3653	3653	3475	3653	3653	3475
Degree Controls	X		X	X		X
Disaggregate Degree Controls		X			X	
Diploma Controls	X	X	X	X	X	X
Gender Controls	X	X	X	X	X	X
Local Wealth Controls	X	X	X	X	X	X
Drop 5% fastest responders			X			X
Complete Pairs Only						
Randomization Reps:	1000					

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C2: Regression Robustness Agreeableness (standardized)

Dependent Variable: Agreeableness (standardized)

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Panel A1: 2022 Sample						
Treatment Assigned	0.047***	0.047***	0.043***	0.059***	0.061***	0.054***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
	[0.000]	[0.000]	[0.003]			
Observations	10859	10859	10316	10859	10859	10316
Panel A2: 2023 Sample						
Treatment Assigned	0.057*	0.050	0.055*	0.088*	-0.050	0.083*
	(0.078)	(0.131)	(0.072)	(0.076)	(0.555)	(0.069)
	[0.402]	[0.442]	[0.629]			
Observations	7976	7976	7577	7976	7976	7577
Panel B1: 2022 without Grand-Est and Pays de la Loire						
Treatment Assigned	0.031*	0.028	0.022	0.034*	0.050*	0.024
	(0.071)	(0.111)	(0.166)	(0.065)	(0.073)	(0.158)
	[0.031]	[0.024]	[0.098]			
Observations	5654	5654	5379	5654	5654	5379
Panel C1: 2022 Sample without Incomplete Strata						
Treatment Assigned	0.051***	0.047***	0.044**	0.065***	0.044**	0.056**
	(0.003)	(0.005)	(0.018)	(0.003)	(0.021)	(0.015)
	[0.051]	[0.056]	[0.124]			
Observations	3793	3793	3600	3793	3793	3600
Panel C2: 2023 Sample without Incomplete Strata						
Treatment Assigned	0.006	-0.018	0.006	0.009	-0.066	0.009
	(0.897)	(0.676)	(0.896)	(0.894)	(0.435)	(0.893)
	[0.900]	[0.731]	[0.758]			
Observations	3653	3653	3475	3653	3653	3475
Degree Controls	X		X	X		X
Disaggregate Degree Controls		X			X	
Diploma Controls	X	X	X	X	X	X
Gender Controls	X	X	X	X	X	X
Local Wealth Controls	X	X	X	X	X	X
Drop 5% fastest responders			X			X
Complete Pairs Only						
Randomization Reps:	1000					

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C3: Regression Robustness Conscientiousness (standardized)

Dependent Variable: Conscientiousness (standardized)

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Panel A1: 2022 Sample						
Treatment Assigned	0.058***	0.057***	0.055***	0.072***	0.083***	0.069***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.001]			
Observations	10859	10859	10316	10859	10859	10316
Panel A2: 2023 Sample						
Treatment Assigned	0.042	0.033	0.037	0.065	0.027	0.056
	(0.131)	(0.269)	(0.166)	(0.132)	(0.710)	(0.166)
	[0.157]	[0.267]	[0.663]			
Observations	7976	7976	7577	7976	7976	7577
Panel B1: 2022 without Grand-Est and Pays de la Loire						
Treatment Assigned	0.056***	0.055***	0.054***	0.062***	0.057*	0.059***
	(0.004)	(0.004)	(0.006)	(0.003)	(0.085)	(0.005)
	[0.008]	[0.006]	[0.125]			
Observations	5654	5654	5379	5654	5654	5379
Panel C1: 2022 Sample without Incomplete Strata						
Treatment Assigned	0.084***	0.069***	0.077***	0.107***	0.070***	0.098***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)
	[0.004]	[0.005]	[0.019]			
Observations	3793	3793	3600	3793	3793	3600
Panel C2: 2023 Sample without Incomplete Strata						
Treatment Assigned	0.026	0.005	0.027	0.040	0.010	0.041
	(0.541)	(0.914)	(0.489)	(0.527)	(0.898)	(0.476)
	[0.498]	[0.922]	[0.649]			
Observations	3653	3653	3475	3653	3653	3475
Degree Controls	X		X	X		X
Disaggregate Degree Controls		X			X	
Diploma Controls	X	X	X	X	X	X
Gender Controls	X	X	X	X	X	X
Local Wealth Controls	X	X	X	X	X	X
Drop 5% fastest responders			X			X
Complete Pairs Only						
Randomization Reps:	1000					

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C4: Regression Robustness Open Mindedness (standardized)

Dependent Variable: Open Mindedness (standardized)

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Panel A1: 2022 Sample						
Treatment Assigned	0.015	0.012	0.014	0.019	0.025	0.018
	(0.178)	(0.264)	(0.217)	(0.169)	(0.254)	(0.207)
	[0.073]	[0.157]	[0.161]			
Observations	10859	10859	10316	10859	10859	10316
Panel A2: 2023 Sample						
Treatment Assigned	-0.025	-0.030	-0.031	-0.038	-0.024	-0.048
	(0.427)	(0.290)	(0.310)	(0.428)	(0.765)	(0.311)
	[0.585]	[0.446]	[0.983]			
Observations	7976	7976	7577	7976	7976	7577
Panel B1: 2022 without Grand-Est and Pays de la Loire						
Treatment Assigned	0.005	0.007	0.003	0.005	0.012	0.003
	(0.742)	(0.639)	(0.832)	(0.740)	(0.577)	(0.830)
	[0.540]	[0.416]	[0.338]			
Observations	5654	5654	5379	5654	5654	5379
Panel C1: 2022 Sample without Incomplete Strata						
Treatment Assigned	0.006	-0.006	0.000	0.007	-0.015	0.001
	(0.752)	(0.723)	(0.980)	(0.742)	(0.476)	(0.979)
	[0.740]	[0.731]	[0.739]			
Observations	3793	3793	3600	3793	3793	3600
Panel C2: 2023 Sample without Incomplete Strata						
Treatment Assigned	0.002	-0.012	-0.012	0.003	-0.065	-0.017
	(0.967)	(0.778)	(0.799)	(0.966)	(0.372)	(0.794)
	[0.975]	[0.804]	[0.867]			
Observations	3653	3653	3475	3653	3653	3475
Degree Controls	X		X	X		X
Disaggregate Degree Controls		X			X	
Diploma Controls	X	X	X	X	X	X
Gender Controls	X	X	X	X	X	X
Local Wealth Controls	X	X	X	X	X	X
Drop 5% fastest responders			X			X
Complete Pairs Only						
Randomization Reps:	1000					

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C5: Regression Robustness Emotional Stability (standardized)

Dependent Variable: Emotional Stability (standardized)

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Panel A1: 2022 Sample						
Treatment Assigned	0.052***	0.054***	0.052***	0.065***	0.082***	0.064***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.003]			
Observations	10859	10859	10316	10859	10859	10316
Panel A2: 2023 Sample						
Treatment Assigned	0.051*	0.056**	0.050*	0.078*	-0.036	0.076*
	(0.065)	(0.045)	(0.071)	(0.064)	(0.605)	(0.068)
	[0.215]	[0.214]	[0.601]			
Observations	7976	7976	7577	7976	7976	7577
Panel B1: 2022 without Grand-Est and Pays de la Loire						
Treatment Assigned	0.046***	0.051***	0.046***	0.051***	0.055**	0.050***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.021)	(0.002)
	[0.038]	[0.018]	[0.115]			
Observations	5654	5654	5379	5654	5654	5379
Panel C1: 2022 Sample without Incomplete Strata						
Treatment Assigned	0.054***	0.054***	0.050***	0.069***	0.066**	0.063**
	(0.003)	(0.008)	(0.009)	(0.005)	(0.016)	(0.012)
	[0.016]	[0.015]	[0.045]			
Observations	3793	3793	3600	3793	3793	3600
Panel C2: 2023 Sample without Incomplete Strata						
Treatment Assigned	0.021	0.020	0.021	0.031	-0.028	0.031
	(0.629)	(0.625)	(0.630)	(0.617)	(0.717)	(0.616)
	[0.618]	[0.637]	[0.619]			
Observations	3653	3653	3475	3653	3653	3475
Degree Controls	X		X	X		X
Disaggregate Degree Controls		X			X	
Diploma Controls	X	X	X	X	X	X
Gender Controls	X	X	X	X	X	X
Local Wealth Controls	X	X	X	X	X	X
Drop 5% fastest responders			X			X
Complete Pairs Only						
Randomization Reps:	1000					

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C6: Regression Robustness Locus of Control (standardized)

Dependent Variable: Locus of Control (standardized)

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Panel A1: 2022 Sample						
Treatment Assigned	0.067***	0.066***	0.064***	0.083***	0.096***	0.080***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]			
Observations	10859	10859	10316	10859	10859	10316
Panel A2: 2023 Sample						
Treatment Assigned	0.002	-0.007	0.003	0.003	-0.078	0.004
	(0.933)	(0.781)	(0.908)	(0.932)	(0.241)	(0.908)
	[0.909]	[0.767]	[0.479]			
Observations	7976	7976	7577	7976	7976	7577
Panel B1: 2022 without Grand-Est and Pays de la Loire						
Treatment Assigned	0.073***	0.072***	0.066***	0.080***	0.081***	0.072***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.002]	[0.002]	[0.014]			
Observations	5654	5654	5379	5654	5654	5379
Panel C1: 2022 Sample without Incomplete Strata						
Treatment Assigned	0.089***	0.079***	0.081***	0.113***	0.098***	0.103***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.001]	[0.001]	[0.001]			
Observations	3793	3793	3600	3793	3793	3600
Panel C2: 2023 Sample without Incomplete Strata						
Treatment Assigned	-0.002	-0.012	-0.003	-0.003	-0.067	-0.005
	(0.958)	(0.782)	(0.938)	(0.957)	(0.343)	(0.936)
	[0.962]	[0.828]	[0.585]			
Observations	3653	3653	3475	3653	3653	3475
Degree Controls	X		X	X		X
Disaggregate Degree Controls		X			X	
Diploma Controls	X	X	X	X	X	X
Gender Controls	X	X	X	X	X	X
Local Wealth Controls	X	X	X	X	X	X
Drop 5% fastest responders			X			X
Complete Pairs Only						
Randomization Reps:	1000					

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C7: Regression Robustness Pursue Studies Yes

Dependent Variable: Pursue Studies Yes

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Panel A1: 2022 Sample						
Treatment Assigned	-0.007	-0.005	-0.007	-0.009	0.002	-0.009
	(0.315)	(0.433)	(0.292)	(0.301)	(0.830)	(0.278)
	[0.321]	[0.473]	[0.970]			
Observations	10859	10859	10316	10859	10859	10316
Panel A2: 2023 Sample						
Treatment Assigned	-0.003	-0.003	-0.004	-0.004	0.017	-0.006
	(0.870)	(0.818)	(0.806)	(0.869)	(0.654)	(0.805)
	[0.816]	[0.740]	[0.610]			
Observations	7976	7976	7577	7976	7976	7577
Panel B1: 2022 without Grand-Est and Pays de la Loire						
Treatment Assigned	-0.023**	-0.020**	-0.026**	-0.026**	-0.008	-0.028***
	(0.017)	(0.039)	(0.011)	(0.013)	(0.540)	(0.008)
	[0.364]	[0.456]	[0.718]			
Observations	5654	5654	5379	5654	5654	5379
Panel C1: 2022 Sample without Incomplete Strata						
Treatment Assigned	-0.005	0.000	-0.010	-0.007	-0.006	-0.013
	(0.621)	(0.970)	(0.309)	(0.605)	(0.602)	(0.287)
	[0.660]	[0.970]	[0.837]			
Observations	3793	3793	3600	3793	3793	3600
Panel C2: 2023 Sample without Incomplete Strata						
Treatment Assigned	0.004	-0.003	-0.000	0.006	-0.004	-0.000
	(0.864)	(0.855)	(0.995)	(0.859)	(0.926)	(0.994)
	[0.866]	[0.877]	[0.797]			
Observations	3653	3653	3475	3653	3653	3475
Degree Controls	X		X	X		X
Disaggregate Degree Controls		X			X	
Diploma Controls	X	X	X	X	X	X
Gender Controls	X	X	X	X	X	X
Local Wealth Controls	X	X	X	X	X	X
Drop 5% fastest responders			X			X
Complete Pairs Only						
Randomization Reps:	1000					

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C8: Regression Robust Log Expected Salary

Dependent Variable: Log Expected Salary

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Panel A1: 2022 Sample						
Treatment Assigned	0.001	0.003	0.002	0.002	-0.007	0.003
	(0.906)	(0.790)	(0.809)	(0.905)	(0.739)	(0.808)
	[0.905]	[0.755]	[0.648]			
Observations	10825	10825	10287	10825	10825	10287
Panel A2: 2023 Sample						
Treatment Assigned	0.037*	0.042*	0.034	0.056*	0.091	0.051*
	(0.082)	(0.051)	(0.103)	(0.076)	(0.141)	(0.094)
	[0.012]	[0.018]	[0.103]			
Observations	7955	7955	7560	7955	7955	7560
Panel B1: 2022 without Grand-Est and Pays de la Loire						
Treatment Assigned	-0.010	-0.008	-0.013	-0.011	-0.057***	-0.014
	(0.482)	(0.590)	(0.330)	(0.473)	(0.007)	(0.317)
	[0.483]	[0.560]	[0.031]			
Observations	5634	5634	5362	5634	5634	5362
Panel C1: 2022 Sample without Incomplete Strata						
Treatment Assigned	-0.011	-0.003	-0.005	-0.014	-0.002	-0.006
	(0.623)	(0.912)	(0.831)	(0.610)	(0.952)	(0.825)
	[0.592]	[0.913]	[0.721]			
Observations	3782	3782	3591	3782	3782	3591
Panel C2: 2023 Sample without Incomplete Strata						
Treatment Assigned	0.054*	0.055*	0.048	0.081*	0.087	0.071*
	(0.077)	(0.069)	(0.103)	(0.067)	(0.195)	(0.085)
	[0.074]	[0.100]	[0.182]			
Observations	3644	3644	3469	3644	3644	3469
Degree Controls	X		X	X		X
Disaggregate Degree Controls		X			X	
Diploma Controls	X	X	X	X	X	X
Gender Controls	X	X	X	X	X	X
Local Wealth Controls	X	X	X	X	X	X
Drop 5% fastest responders			X			X
Complete Pairs Only						
Randomization Reps:	1000					

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C9: Regression Robust Subjective 6-Month Job-Find Probability

Dependent Variable: Subjective 6-Month Job-Find Probability

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Panel A1: 2022 Sample						
Treatment Assigned	0.008**	0.008***	0.007**	0.010**	0.009*	0.009**
	(0.022)	(0.009)	(0.038)	(0.018)	(0.078)	(0.032)
	[0.136]	[0.098]	[0.180]			
Observations	10859	10859	10316	10859	10859	10316
Panel A2: 2023 Sample						
Treatment Assigned	0.001	-0.003	0.000	0.002	-0.036*	0.001
	(0.897)	(0.768)	(0.966)	(0.897)	(0.093)	(0.966)
	[0.933]	[0.786]	[0.221]			
Observations	7976	7976	7577	7976	7976	7577
Panel B1: 2022 without Grand-Est and Pays de la Loire						
Treatment Assigned	0.014***	0.015***	0.012**	0.015***	0.016***	0.013**
	(0.008)	(0.002)	(0.023)	(0.006)	(0.002)	(0.019)
	[0.068]	[0.022]	[0.078]			
Observations	5654	5654	5379	5654	5654	5379
Panel C1: 2022 Sample without Incomplete Strata						
Treatment Assigned	0.012**	0.013***	0.010**	0.015***	0.013**	0.013**
	(0.012)	(0.002)	(0.029)	(0.007)	(0.021)	(0.020)
	[0.061]	[0.011]	[0.190]			
Observations	3793	3793	3600	3793	3793	3600
Panel C2: 2023 Sample without Incomplete Strata						
Treatment Assigned	-0.013	-0.016	-0.014	-0.019	-0.040*	-0.020
	(0.294)	(0.171)	(0.249)	(0.277)	(0.073)	(0.239)
	[0.343]	[0.253]	[0.160]			
Observations	3653	3653	3475	3653	3653	3475
Degree Controls	X		X	X		X
Disaggregate Degree Controls		X			X	
Diploma Controls	X	X	X	X	X	X
Gender Controls	X	X	X	X	X	X
Local Wealth Controls	X	X	X	X	X	X
Drop 5% fastest responders			X			X
Complete Pairs Only						
Randomization Reps:	1000					

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C10: Regression Robust Preparedness for Job-Seaerch (factor weight standardized)

Dependent Variable: Preparedness for Job-Search (factor weight standardized)

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Panel A1: 2022 Sample						
Treatment Assigned	0.041***	0.043***	0.037***	0.051***	0.049***	0.046***
	(0.001)	(0.000)	(0.003)	(0.000)	(0.008)	(0.002)
	[0.010]	[0.011]	[0.018]			
Observations	10859	10859	10316	10859	10859	10316
Panel A2: 2023 Sample						
Treatment Assigned	-0.029	-0.042	-0.037	-0.045	-0.137*	-0.056
	(0.346)	(0.152)	(0.199)	(0.332)	(0.082)	(0.183)
	[0.156]	[0.067]	[0.190]			
Observations	7976	7976	7577	7976	7976	7577
Panel B1: 2022 without Grand-Est and Pays de la Loire						
Treatment Assigned	0.061***	0.062***	0.051***	0.067***	0.045*	0.056***
	(0.000)	(0.000)	(0.002)	(0.000)	(0.063)	(0.001)
	[0.085]	[0.032]	[0.188]			
Observations	5654	5654	5379	5654	5654	5379
Panel C1: 2022 Sample without Incomplete Strata						
Treatment Assigned	0.042**	0.044**	0.034*	0.053***	0.064***	0.043*
	(0.015)	(0.014)	(0.099)	(0.005)	(0.006)	(0.069)
	[0.018]	[0.006]	[0.027]			
Observations	3793	3793	3600	3793	3793	3600
Panel C2: 2023 Sample without Incomplete Strata						
Treatment Assigned	-0.055	-0.068	-0.064	-0.082	-0.159*	-0.096
	(0.210)	(0.106)	(0.126)	(0.197)	(0.053)	(0.118)
	[0.212]	[0.138]	[0.108]			
Observations	3653	3653	3475	3653	3653	3475
Degree Controls	X		X	X		X
Disaggregate Degree Controls		X			X	
Diploma Controls	X	X	X	X	X	X
Gender Controls	X	X	X	X	X	X
Local Wealth Controls	X	X	X	X	X	X
Drop 5% fastest responders			X			X
Complete Pairs Only						
Randomization Reps:	1000					

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C11: Regression Robust Expected Probability of Liking Job

Dependent Variable: Expected Probability of Liking Job

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Panel A1: 2022 Sample						
Treatment Assigned	0.009***	0.010***	0.008**	0.011***	0.013**	0.010**
	(0.006)	(0.002)	(0.014)	(0.004)	(0.021)	(0.011)
	[0.023]	[0.021]	[0.090]			
Observations	10859	10859	10316	10859	10859	10316
Panel A2: 2023 Sample						
Treatment Assigned	0.018**	0.013*	0.014*	0.028**	0.021	0.022
	(0.031)	(0.077)	(0.094)	(0.036)	(0.278)	(0.100)
	[0.078]	[0.147]	[0.249]			
Observations	7976	7976	7577	7976	7976	7577
Panel B1: 2022 without Grand-Est and Pays de la Loire						
Treatment Assigned	0.014***	0.014***	0.012**	0.015***	0.001	0.013**
	(0.008)	(0.007)	(0.015)	(0.007)	(0.957)	(0.012)
	[0.192]	[0.158]	[0.924]			
Observations	5654	5654	5379	5654	5654	5379
Panel C1: 2022 Sample without Incomplete Strata						
Treatment Assigned	0.009	0.010*	0.007	0.012	0.008	0.010
	(0.119)	(0.068)	(0.170)	(0.109)	(0.287)	(0.156)
	[0.177]	[0.133]	[0.592]			
Observations	3793	3793	3600	3793	3793	3600
Panel C2: 2023 Sample without Incomplete Strata						
Treatment Assigned	0.018	0.012	0.017	0.028*	0.018	0.026
	(0.112)	(0.243)	(0.127)	(0.094)	(0.346)	(0.108)
	[0.151]	[0.302]	[0.302]			
Observations	3653	3653	3475	3653	3653	3475
Degree Controls	X		X	X		X
Disaggregate Degree Controls		X			X	
Diploma Controls	X	X	X	X	X	X
Gender Controls	X	X	X	X	X	X
Local Wealth Controls	X	X	X	X	X	X
Drop 5% fastest responders			X			X
Complete Pairs Only						
Randomization Reps:	1000					

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C12: Regression Robust Expected Probability of Securing Permanent Contract

Dependent Variable: Expect Permanent Contract

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Panel A1: 2022 Sample						
Treatment Assigned	-0.009	-0.009	-0.009	-0.011	-0.022**	-0.011
	(0.129)	(0.129)	(0.124)	(0.128)	(0.039)	(0.124)
	[0.091]	[0.083]	[0.078]			
Observations	10859	10859	10316	10859	10859	10316
Panel A2: 2023 Sample						
Treatment Assigned	-0.012	-0.010	-0.008	-0.018	0.010	-0.012
	(0.367)	(0.419)	(0.553)	(0.366)	(0.791)	(0.551)
	[0.509]	[0.602]	[0.932]			
Observations	7976	7976	7577	7976	7976	7577
Panel B1: 2022 without Grand-Est and Pays de la Loire						
Treatment Assigned	-0.012	-0.010	-0.013	-0.013	-0.027*	-0.014*
	(0.117)	(0.189)	(0.103)	(0.115)	(0.062)	(0.099)
	[0.093]	[0.071]	[0.134]			
Observations	5654	5654	5379	5654	5654	5379
Panel C1: 2022 Sample without Incomplete Strata						
Treatment Assigned	-0.007	-0.010	-0.012	-0.009	-0.019	-0.015
	(0.484)	(0.342)	(0.243)	(0.445)	(0.180)	(0.183)
	[0.506]	[0.395]	[0.357]			
Observations	3793	3793	3600	3793	3793	3600
Panel C2: 2023 Sample without Incomplete Strata						
Treatment Assigned	-0.001	0.005	0.003	-0.001	0.006	0.005
	(0.973)	(0.791)	(0.882)	(0.972)	(0.886)	(0.879)
	[0.977]	[0.818]	[0.967]			
Observations	3653	3653	3475	3653	3653	3475
Degree Controls	X		X	X		X
Disaggregate Degree Controls		X			X	
Diploma Controls	X	X	X	X	X	X
Gender Controls	X	X	X	X	X	X
Local Wealth Controls	X	X	X	X	X	X
Drop 5% fastest responders			X			X
Complete Pairs Only						
Randomization Reps:	1000					

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C13: Non-Cognitive Skills by Sex (Part 1)

Part 1: Non-Cognitive Skills by Sex

	(1) Men (OLS)	(2) Men (IV)	(3) Women (OLS)	(4) Women (IV)
Extraversion (standardized) 2022				
Treatment Assigned	0.052***	0.063***	0.035**	0.046**
	(0.000)	(0.000)	(0.032)	(0.030)
	[0.034]		[0.002]	
Observations	6200	6200	4659	4659
Extraversion (standardized) 2023				
Treatment Assigned	0.037	0.057	0.008	0.012
	(0.204)	(0.200)	(0.846)	(0.845)
	[0.710]		[0.750]	
Observations	4549	4549	3427	3427
Agreeableness (standardized) 2022				
Treatment Assigned	0.062***	0.075***	0.028	0.036
	(0.000)	(0.000)	(0.148)	(0.151)
	[0.000]		[0.045]	
Observations	6200	6200	4659	4659
Agreeableness (standardized) 2023				
Treatment Assigned	0.073*	0.111*	0.038	0.059
	(0.090)	(0.092)	(0.400)	(0.394)
	[0.345]		[0.473]	
Observations	4549	4549	3427	3427
Conscientiousness (standardized) 2022				
Treatment Assigned	0.072***	0.087***	0.039**	0.051**
	(0.000)	(0.000)	(0.036)	(0.037)
	[0.004]		[0.005]	
Observations	6200	6200	4659	4659
Conscientiousness (standardized) 2023				
Treatment Assigned	0.037	0.057	0.055	0.085
	(0.218)	(0.224)	(0.264)	(0.261)
	[0.177]		[0.304]	
Observations	4549	4549	3427	3427
Degree Controls	X	X	X	X
Diploma Controls	X	X	X	X
Economic Controls	X	X	X	X
Randomization Reps:	1000			

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C14: Non-Cognitive Skills by Sex (Part 2)

Part 2: Non-Cognitive Skills by Sex

	(1) Men (OLS)	(2) Men (IV)	(3) Women (OLS)	(4) Women (IV)
Open Mindedness (standardized) 2022				
Treatment Assigned	0.012	0.014	0.021	0.027
	(0.373)	(0.369)	(0.238)	(0.227)
	[0.255]		[0.113]	
Observations	6200	6200	4659	4659
Open Mindedness (standardized) 2023				
Treatment Assigned	0.000	0.001	-0.050	-0.076
	(0.991)	(0.991)	(0.356)	(0.365)
	[0.988]		[0.636]	
Observations	4549	4549	3427	3427
Emotional Stability (standardized) 2022				
Treatment Assigned	0.066***	0.079***	0.036**	0.046**
	(0.000)	(0.000)	(0.041)	(0.046)
	[0.001]		[0.046]	
Observations	6200	6200	4659	4659
Emotional Stability (standardized) 2023				
Treatment Assigned	0.031	0.047	0.086	0.132
	(0.255)	(0.251)	(0.100)	(0.104)
	[0.674]		[0.135]	
Observations	4549	4549	3427	3427
Locus of Control (standardized) 2022				
Treatment Assigned	0.083***	0.100***	0.045***	0.059***
	(0.000)	(0.000)	(0.003)	(0.003)
	[0.000]		[0.003]	
Observations	6200	6200	4659	4659
Locus of Control (standardized) 2023				
Treatment Assigned	-0.003	-0.005	0.009	0.014
	(0.921)	(0.920)	(0.831)	(0.830)
	[0.902]		[0.776]	
Observations	4549	4549	3427	3427
Degree Controls	X	X	X	X
Diploma Controls	X	X	X	X
Economic Controls	X	X	X	X
Randomization Reps:	1000			

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C15: Expectations by Sex (Part 1)

Part 1: Expectations by Sex

	(1) Men (OLS)	(2) Men (IV)	(3) Women (OLS)	(4) Women (IV)
Continue Studies Yes (2022)				
Treatment Assigned	-0.010	-0.012	-0.006	-0.007
	(0.304)	(0.290)	(0.408)	(0.401)
	[0.369]		[0.313]	
Observations	6200	6200	4659	4659
Continue Studies Yes (2023)				
Treatment Assigned	-0.007	-0.011	0.008	0.013
	(0.743)	(0.742)	(0.670)	(0.665)
	[0.645]		[0.578]	
Observations	4549	4549	3427	3427
Log Expected Salary (2022)				
Treatment Assigned	0.000	0.001	0.000	0.000
	(0.973)	(0.973)	(0.999)	(0.999)
	[0.957]		[0.999]	
Observations	6183	6183	4642	4642
Log Expected Salary (2023)				
Treatment Assigned	0.065**	0.099**	0.009	0.014
	(0.016)	(0.020)	(0.778)	(0.775)
	[0.025]		[0.725]	
Observations	4543	4543	3412	3412
Subjective 6-Month Job-Find Probability (2022)				
Treatment Assigned	0.012**	0.014**	0.003	0.004
	(0.013)	(0.010)	(0.427)	(0.425)
	[0.328]		[0.336]	
Observations	6200	6200	4659	4659
Subjective 6-Month Job-Find Probability (2023)				
Treatment Assigned	0.005	0.008	-0.005	-0.008
	(0.662)	(0.661)	(0.643)	(0.634)
	[0.832]		[0.656]	
Observations	4549	4549	3427	3427
Degree Controls	X	X	X	X
Diploma Controls	X	X	X	X
Economic Controls	X	X	X	X
Randomization Reps:	1000			

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C16: Expectations by Sex (Part 2)

Part 2: Expectations by Sex

	(1) Men (OLS)	(2) Men (IV)	(3) Women (OLS)	(4) Women (IV)
Preparedness for Job-Search (2022)				
Treatment Assigned	0.042**	0.051***	0.041***	0.054***
	(0.011)	(0.007)	(0.007)	(0.008)
	[0.227]		[0.022]	
Observations	6200	6200	4659	4659
Preparedness for Job-Search (2023)				
Treatment Assigned	-0.014	-0.022	-0.050	-0.077
	(0.726)	(0.722)	(0.275)	(0.257)
	[0.573]		[0.120]	
Observations	4549	4549	3427	3427
Probability of Liking Job (2022)				
Treatment Assigned	0.013***	0.016***	0.003	0.004
	(0.001)	(0.000)	(0.450)	(0.448)
	[0.054]		[0.370]	
Observations	6200	6200	4659	4659
Probability of Liking Job (2023)				
Treatment Assigned	0.014	0.021	0.023**	0.036**
	(0.165)	(0.174)	(0.032)	(0.036)
	[0.248]		[0.072]	
Observations	4549	4549	3427	3427
Expect Permanent Contract (2022)				
Treatment Assigned	-0.002	-0.003	-0.018**	-0.023**
	(0.736)	(0.734)	(0.047)	(0.047)
	[0.677]		[0.017]	
Observations	6200	6200	4659	4659
Expect Permanent Contract (2023)				
Treatment Assigned	-0.003	-0.004	-0.028*	-0.043*
	(0.884)	(0.883)	(0.094)	(0.094)
	[0.856]		[0.273]	
Observations	4549	4549	3427	3427
Degree Controls	X	X	X	X
Diploma Controls	X	X	X	X
Economic Controls	X	X	X	X
Randomization Reps:	1000			

Note: Robust standard errors were clustered at the strata level. P-values are reported in parentheses. Randomization inference p-values are reported in square brackets. "Randomization Reps" gives the number of permutations performed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.