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Mentoring as a dose treatment: frequency matters.

Evidence from a French mentoring program*

Mentoring
Treatment effects
Dropout

We evaluate how the impact of a mentoring program in French disadvantaged high schools varies with the intensity of the program. Given that, in general, the only significant effect was observed by full attendance to all meetings, we argue that the treatment dose matters. Thus, while the original evaluation program was designed as a randomized experiment to balance control and treated individuals (those who were offered the mentoring scheme, with different degree of program participation), we motivate the use of continuous and multi-valued treatment effects models to estimate the dose response function. The program shows that information about prospective labor market opportunities feeds back positively into academic performance. However, it has a negative effect on job self-esteem, suggesting that acquiring information on job market prospects updates students' priors on their skills and possibilities and that the students might be updating rationally.

Programas de tutoría como un tratamiento dosificado: la frecuencia importa.

Evidencia de un programa de tutoría francés

Tutorías
Tratamiento
Abandono escolar

Se evalúa el impacto de un programa de tutoría en escuelas secundarias francesas y cómo varía con la intensidad del programa. Dado que, en general, el único efecto estadísticamente significativo corresponde a los que atienden todas las sesiones, se argumenta que la dosis del tratamiento importa. Así, mientras el programa original estaba pensado como un experimento aleatorio para balancear grupo de control y tratamiento, motivamos el uso de modelos de tratamiento multivariado y continuo para estimar la función de dosis. El programa muestra información de potenciales trabajadores y afecta positivamente la performance escolar. Sin embargo, tiene un efecto negativo sobre la auto-estima, lo que sugiere que al adquirir información sobre el mercado de trabajo los estudiantes actualizan su evaluación de sus propias habilidades y posibilidades en forma racional.

JEL CODE C31, I22, I24, I26, I28

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Índice

1 Introduction

Transition into the labor market is far from being a smooth process for the youth of marginalized areas. Individual investment choices in, first, pursuing additional studies after high-school and second, in labor market search efforts, hence influencing job market outcomes, might be hindered if school dropout rates are high.[1] The existing literature provides two types of explanations for high dropout rates in high-school, related on the one hand to constrained access to credit and, on the other hand to students' aspiration and information. Firstly, despite the recognition of a profitable investment, families might not have the financial means to sustain their children during their studies and, for this reason, children decide to dropout. This is confirmed by some studies showing a positive effect of financial aids on university enrollment, such as Dynarski (2003), Bettinger (2004), Dearden, Emmerson, Frayne, and Meghir (2005) and Rodríguez-Planas (2012). Secondly, the social and cultural environment might play a role in explaining the weak aspirations of youngsters that decide not to continue their studies. Individuals might have imperfect information about the education system or they might underestimate its potential in terms of salary and unemployment protection, and, as a consequence, they might take disadvantageous decisions. Lack of motivation might be a reason for dropping out (Eckstein and Wolpin, 2003). Social connections and peer group effects are important in this sense: when making educational and professional choices, young people tend to

[1] Formally, dropping out of school could be also part of the potential choices in terms of educational investment.

trust their closer counterparts such as their family and their friends (Tacsir, 2010), hence reproducing the same patterns of the own social and cultural capital, as well as the bounded aspirations.[2] Jensen (2010) hypothesized that enrollment in higher education varies on the basis of partial, imperfect or limited information.

Mentoring has the objective of tackling those problems through the pairing of an older or more experienced individual as guide or example with a student in order to (i) improve the student's emotional and social well-being; (ii) improve the student's cognitive skills (i. e., increasing school performance); (iii) provide the student with a role model and contribute to their formation. Several empirical studies focus on evaluating mentoring or similar schemes, and identifying the underlying reasons for dropout.[3]

In this study, we evaluate the impact of a mentoring program in French high-schools on academic achievement, job market knowledge, and career-related goals of the students mentored. The program follows high-school students with underprivileged social background in their academic orientation and in the drawing up of their professional incipient projects. This program is grounded into the general consensual assumption in the literature on the role of the socio-economic background determinants in educational

[2] The economics of identity literature indicates the possibility that students have low aspirations because they have different preferences along with lower chances of success than socially advantaged students. In that sense disadvantaged students would have low aspirations but that would be rational, i. e., utility-maximizing. Our results presented in Section 5 point out in a different direction.

[3] See, for instance, Heckman and Rubinstein (2001), Bénabou and Tirole (2002), Attanasio and Kaufmann (2009), Bettinger, Long, Oreopoulos, and Sanbonmatsu (2012), Hoxby and Avery (2013, 2015), Holmstrom, Russell, and Clare (2015) and Goux, Gurgand, and Maurin (2017).

choices, educational social inequalities and professional integration. This particular mentoring program was evaluated by the Poverty Action Lab (J-PAL) in order to analyze the effect of the mentoring scheme on several potential outcomes, which are themselves the channels for future labor market performance success (see Behaghel, Chiodi, and Gurgand, 2013, for a description). The database we use contains a rich set of variables regarding the characteristics of the students thus allowing us to link the effect of the mentoring program with student specific information. In this paper, we are interested in the particular heterogeneity that arises from the fact that mentoring programs vary in intensity and frequency depending on the quantity and nature of the mentoring sessions. Thus we evaluate mentoring from a multi-valued and continuous treatment perspective, where the number of sessions attended is the amount or dose of treatment. The particular data for the evaluation clearly reflects high attrition rates and different rates of participation, even for the so-defined treatment group. That is, students starting the mentoring program for some sessions, then not completing all four sessions. This shows that if the mentoring program was planned for a given number of sessions, attending some but not all may have provided students partial or incomplete information, resulting in different effects from what was originally planned. Then, there may be differences in outcomes depending on the number of attended sessions, which may be informative on the optimal duration of treatments.

We implement multi-valued treatment effects (MTE) and continuous treatment effects (CTE) models to estimate the outcome of this program when the dose (attendance) is different from a binary indicator. In those models, programs can be evaluated not only by treatment indicator(s) but also according to the quality or length of the treatment(s). Multi-valued and continuous treatments (such as those indexed by dose, exposure, duration, or frequency) arise very often in practice, especially in observational studies. Importantly, such treatments lead to effects that are naturally described by curves (e. g., dose-response curves as functional of the treatment dose).[4] Since dose is a choice variable given by individuals' self-selection, the identification strategy in both MTE and CTE relies on the unconfoundedness assumption after we condition on exogenous covariates.

This study finds that, if available, frequency, intensity and/or duration of treatment are important factors to consider in treatment analysis. In general, we find that the only significant effect is given by full attendance to all meetings. These results show that information about prospective labor market opportunities feeds back positively into academic performance. The mentoring program is also effective in augmenting students' ambition to

[4]Many papers in the literature concentrate on discrete treatments, i. e., binary or multi-valued treatment assignments. On the binary treatment effects (TE) models, Hahn (1998), Heckman, Ichimura, Smith, and Todd (1998), Hirano, Imbens, and Ridder (2003), Abadie and Imbens (2006), Imbens, Newey, and Ridder (2006), and Li, Racine, and Wooldridge (2009) study efficient estimation of the average treatment effects (ATE). There is also literature on estimation of multi-valued TE, see e. g., Imbens (2000), Lechner (2001), Cattaneo (2010) and Cattaneo, Drukker, and Holland (2013). In addition, Hirano and Imbens (2004) develop a generalized propensity score (GPS) for continuous average treatment models. Flores (2007) proposes nonparametric estimators for average dose-response functions (ADRF). Florens, Heckman, Meghir, and Vytlacil (2008) consider identification of ATE using control functions. Flores, Flores-Lagunes, Gonzalez, and Neumann (2012) estimate causal effects of different lengths of exposure to academic and vocational instruction. Galvao and Wang (2015) and Alejo, Galvao, and Montes-Rojas (2018) develop general estimators for CTE based on Z-estimators. Bia and Kerm (2014) develop semi-parametric estimators for the estimation of dose-response functions using penalized and radial spline models.

continue studying after secondary school. The program, however, has a negative effect on job self-esteem, suggesting that acquiring information on job market prospects updates students' priors on their skills and possibilities.

The paper is organized as follows. Section 2 describes the mentoring program we analyze. Section 3 presents the econometric methods on treatment effects for multi-valued and continuous treatments. Section 4 provides summary statistics of the dataset. Section 5 reports the econometric analysis. Section 6 concludes and discusses policy implications.

2 The mentoring program

In France as in other countries, there is a strong correlation between the level of education and social background. For instance, 76% of children from the working class leave the educational system with at the best a secondary school degree, while this is the case for only 36% of children from managerial-class backgrounds follow the same path. Duru-Bellat, Jarousse, and Mingat (1993) study results show that 96% of children from a managerial-class background who had an average grade between 9 and 10 in their last year of secondary school pursued their schooling in a general high school, while only 37% of children of blue-collar parents. These proportions are still of 97% and 65%, respectively, for those who had an average grade between 10 and 12. High schools in France are divided in two parts (11 to 15 years old, and 15 to 18 years old). Once they finish the first part of the secondary school, students are required to make orientation choices that usually do not match with their actual academic achievement, and are based on the grades obtained at the end of the first part of the secondary school diploma (the "Brevet" diploma).

Furthermore, the French Education and Youth Ministry grants subsidies to schools located in disadvantaged areas, and those subsidies are often used to offer mentoring programs to expand students' knowledge about the job market and employment. "Mentoring Assistance and Orientation" was one such program, and it was provided by a non-profit volunteer organization.[5] Established in 2006, the program aims to provide guidance through contact with volunteer professionals in various fields.

Students were individually assigned to a mentor in accordance with their interests. These volunteers mentor students in the second part of the high school. The sessions between the mentor and the student are dedicated to the discussion around i) the schooling track choices (in France there are different discipline tracks: literature and languages, social sciences and sciences, in a nutshell), ii) the academic performance during the school year and potential difficulties faced by the students, and more broadly iii) the construction of the future professional career (choice, information of jobs and on diplomas needed, on investment channels for job search and efforts needed to entry the labor market). They do also can share a cultural or a sport activity. The mentors are actively engaged in the labor market and arise from different areas, and they do receive a couple of sessions of information with the NGO.

[5] A description of the program can be found at the association website `http://www.actenses.fr` (in French).

The mentor helps the mentee to determine her professional path by sharing information about the professional field of interest, job opportunities, and requirements for professional success. The exchange between the mentor and the mentee was designed to be complementary to the career information that is already given by the orientation adviser in the school. Schools were eligible because they were part of the "zone éducation prioritaire", i. e., reside in a disruptive environment. In general, dropout rates are very high in those schools and the orientation choices the students need to make are of concern as they represent a key decision for their schooling and professional aspirations. The mentors could meet their mentees outside the four sessions organized by the association and could also communicate over the phone or by email. Unfortunately, we lack data on the characteristics of the mentors and of the meetings outside the sessions organized by the association. In very few cases, the pair was dissolved and the organization found a replacement. Not all the students of the treatment classes have a mentor and in that case the organization members acted as mentors.

In order to evaluate this program, J-PAL researchers examined the impact of the Mentoring Assistance and Orientation program on academic achievement, job market knowledge, and career-related goals for 2,500 students in 22 high schools.[6] Schools were phased into the program over a two year period. All schools and classes were randomly assigned to control

[6] See Behaghel, Chiodi, and Gurgand (2013) and the brief description of the program in `https://www.povertyactionlab.org/evaluation/career-mentoring-secondary-students-france-actenses` and the evaluation `https://www.experimentation-fej.injep.fr/IMG/pdf/Actenses_rapport_jan2013.pdf`.

and treatment schools on a two-step randomization scheme.[7] First, schools were randomly assigned to either a treatment or a control group. Second, within each treatment school, there was one random treatment class and one random control class the first year of the evaluation and two control classes the second year. Symmetrically, every control school had two control classes the first year of the evaluation as well as one treatment class and one control class the second year. Both groups were tracked with a baseline individual questionnaire before randomization, and then 12 months after randomization.[8]

Students in the treatment classes were offered a mentor. The association organized four mentor/mentee meetings over the school year. The mentors could communicate by phone or e-mail with their mentees and the pairs could also meet outside of the activities organized by the association if they wished. Researchers collected data from administrative records on grades, absence and pupil behavior, and conducted surveys to measure students' general knowledge about the professional world (types of jobs and the requirements to enter the respective fields), construction and evolution of the student's professional plans, self-esteem and motivation.

[7] This design allows to evaluate the spillover effects as well. Since the program consisted mainly on information provision, we checked for any diffusion to students not involved in the program and found no effect.

[8] The administrative data was collected at the same time as the survey data.

3 Multi-valued and continuous treatment effects models

The model's objective is to assess how an outcome variable changes as the dose of some treatment variable varies. The dose is denoted by t, where $t \in \mathcal{T}$, a real interval, and the outcome is denoted by $Y(t)$. More specifically, for each $t \in \mathcal{T}$, $Y(t)$ is the outcome when the dose of treatment is t. Thus, we define the random process $Y(t)$ as t varies in $\mathcal{T}$. In the binary treatment case $\mathcal{T} = \{0, 1\}$. In this paper, we evaluate the multi-valued case where $\mathcal{T}$ is either the number of attended sessions, or a continuous index generated from the number of attended sessions and the quality of those. Thus it will be either multi-valued discrete or continuous.

An important parameter of interest when the treatment is continuous is the average dose response function (ADRF), defined as

$$ADRF(t) := E[Y(t)], \tag{1}$$

the unconditional mean for a given value of treatment t. Thus, the ADRF summarizes the potential response of each dose of a specified outcome of interest $Y(t)$ to each dose of magnitude $t \in \mathcal{T}$.

From the ADRF, one can learn about another interesting parameter, the average continuous treatment effect (ACTE), which is defined as

$$\Delta_{\tau}(t, t') := ADRF(t) - ADRF(t'). \tag{2}$$

The ACTE captures the difference of the ADRFs for two given different levels of treatment, t and t'. Of particular interest is to analyze the ACTE for a fixed change in the dose, say δ, over the doses $t \in \mathcal{T}$ as

$$D_\tau(t,\delta) := \Delta_\tau(t+\delta, t). \tag{3}$$

Unfortunately, as usual in the treatment effects literature, one cannot observe $Y(t)$ for all $t \in \mathcal{T}$. Rather, only a single $Y(t_0)$ can be observed, where t_0 is the realization of a random variable T. Hence, if assignment to treatment status depends on potential outcomes, as it is usual in economic and other non-experimental problems, then selection biases arise as the observed outcomes might not be the result of the dose itself but of a self-assignment into treatment. In our case, while the evaluation experiment was itself designed as an experiment with random assignment, dropouts and self-selection may produce bias in the estimation of the ADRF. To solve this problem, it is common in the treatment effects literature to assume the existence of a set of random variables X conditional on which $Y(t)$ is independent from T for all $t \in \mathcal{T}$. Thus conditional on observable variables, observed outcomes can be given a causal interpretation. This is referred to as the ignorability condition or weak unconfoundedness assumption in the literature. Finally, we need to combine the results for X to obtain an unconditional TE. By the law of iterated expectations, unconditional expectations can be recovered.

Imbens (2000), Lechner (2001), Cattaneo (2010) and Cattaneo, Drukker, and Holland (2013) evaluate the case of multi-valued treatment effects and consider different consistent estimators of both ADRF and ACTE. In this case, the intuition behind the identification conditions are similar to those of the binary treatment case. For the continuous case, Hirano and Imbens (2004) propose to obtain consistent estimators of the ADRF by first defining the generalized propensity score as the conditional density function of T, conditional on X, $f_{T|X}(t|X)$, which is in fact the continuous generalization of the propensity score of binary treatment models. According to the ignorability condition, we only need to condition on $f_{T|X}(t|X)$ and use $E[Y(t)] = E[Y(t)|t, X] = E[Y(t)|f_{T|X}(t|X)]$. Thus the authors propose a two-step estimator where, in a first step, they estimate $f_{T|X}(t|X)$ and in a second step, they propose a parametric approximation of the model $E[Y(t)|f_{T|X}(t|X)]$ that is obtained by running a regression of Y on a polynomial of T, $f_{T|X}(t|X)$ and its interactions. Flores, Flores-Lagunes, Gonzalez, and Neumann (2012) use a nonparametric kernel estimator of the same conditional model, where the kernel is defined by weighting the distance of T to the specific value of treatment t to be evaluated.

We implement these estimators with the `teffects` STATA package to evaluate multi-valued treatment effects approach (regression adjustment option), following the Cattaneo (2010) and Cattaneo, Drukker, and Holland (2013) models. We use the STATA command `doseresponse` to implement Hirano and Imbens (2004) estimator (see Bia and Mattei (2008)) of the ADRF and ACTE. For robustness checks, we also implement the ADRF of Flores, Flores-Lagunes, Gonzalez, and Neumann (2012) with the STATA command `drf` (see Bia, Flores, Flores-Lagunes, and Mattei (2014)) and we compare both with the unconditional nonparametric regression estimator of a regression of Y on T (local linear polynomial regression, `lpoly`) in order to highlight the effect of the conditioning set. Although not reported, similar results are obtained with other estimators for CTE such as Bia and Kerm (2014) and Alejo, Galvao, and Montes-Rojas (2018).

4 Data and summary statistics

The program evaluation was designed to evaluate a binary treatment, making use of a randomization strategy, by comparing different treatment and control groups. The J-PAL evaluation found weak or no evidence of significant treatment effects. The weak effects reported were explained by the low intensity of the intervention evaluated and marked heterogeneity in exposure. Moreover, it was noted that not all students had a mentor, and the mentor-mentee relationship took time to develop. This paper focuses explicitly on this issue of heterogeneity and intensity of treatment.

The sample consists of 636 students that were followed over a one-year period. Table 1 presents the descriptive statistics of the treatment variable, both treated as continuous (left columns) and discrete (right columns). While the program was designed for 4 sessions throughout the year, the number of attendances varies uniformly on the range $\{0, 1, 2, 3, 4\}$. Note that the number of meetings could be zero even if the student was assigned to treatment, provided he/she did not attend any session. Moreover, the nature of those meetings varied as some meetings were with the assigned mentor, while others consisted in general sessions because the assigned mentor was not available. We create a continuous treatment variable T that counts the number of sessions attended in the first year of the program. If the meeting was with the assigned mentor, the meeting had a value of 1, while if it was attendance to a meeting where the mentor was not available, a value of 1/3 as the treatment was therefore less intense. Second, we also define a discrete treatment variable as an alternative measure that only counts the number of attended sessions, imputing the same value of 1 if the mentor were present or not, for which we use the multi-valued and discrete treatment analysis.

Regarding the outcomes of interest, the data collected contains heterogeneous information with respect to the individual's academic performance, motivation and general attitude towards the labor market. To reduce the dimensionality of the problem, some variables are taken as the first factor in a principal component factor (PCF) analysis. Other outcome variables are the result of standard scores constructed from the questionnaires. In all cases, the variables are standardized by subtracting the sample mean and dividing it by the sample standard deviation. The effects are then interpreted in units of standard deviations for each outcome variable. The variables considered as outcome variables are:

- *Overall grades*: Overall average grades at the end of the year.

- *Absences*: Absences over the school year.

- *Jobs research initiative*: predicted factor from PCF analysis using a question on whether the mentee made some research about her preferred job, and whether he/she talked about that with the mentor.

- *Extrinsic motivation* and *Intrinsic motivation*: index on motivation obtained through a sum of questions.[9] Intrinsic motivation measures the adherence of young people to a series of reasons to attend high school (e. g., "because I like and I find it satisfying to learn new things"); the extrinsic motivation measures in the same way the adherence to reasons such as to have the possibility to get a better job later in her/his life.

- *Career choice*: the student knows what career he/she wants to follow (binary outcome).

- *Career choice, concrete*: the mentee is able to provide examples of the career he/she wants to pursue (binary outcome).

- *Self-esteem*: scores which are divided in general, school and work-related. The score is a sum and is obtained from a three series of questions. For the "general self-esteem", examples of questions are "Do you feel like you would like to be someone else?". For the self-esteem related to school, questions are "To what extent do you consider yourself like a student that can do homework rapidly?". For the "job market" part, questions such as "Do you consider yourself among the young people having the impression of not being old enough to have a job and keep it?"

[9] The sources used in the questionnaires to build the psychometric outcomes are diverse and they are available upon request. For instance regarding extrinsic and intrinsic motivation and self-esteem we use an adaptation of Guay's Harter's questions respectively (see Harter, 1982; PierreHumbert, Plancherel, and Caretta, 1987; Guay, Chanal, Ratelle, Marsh, Lorose, and Boivin, 2012).

- *Job market knowledge*: knowledge index on the job market. The score is obtained by summing the number of correct answers to a series of questions on the job market and sector of studies, e. g., questions relative to the necessary education and initial salary for a list of jobs, to the proportion of young people who have a permanent contract 3 years after the end of 3 types of studies, to the modifications to do in a fake CV, to questions he/she should expect in an interview.

- *Ambition*: ambition on continuing studying after secondary school. The variable is constructed following the question "Which level of studies do you think you will really achieve?" with "Bac +3" (Bac is the high school diploma) as a threshold that corresponds to the median ambition (it is a binary outcome).

Following Behaghel, Chiodi, and Gurgand (2013), the following conditional variables X were used for the unconfoundedness identification strategy: baseline grades in Maths and French, schooling level of their parents (a dummy for white-collar, and one for no participation in the labor force), sex, a French nationality dummy, and over-age delayed school year and a dummy for repeated last year. To this set of variables we add five individual variables related to motivation and self-esteem taken at baseline (pre-treatment) that may help making the unconfoundedness assumption plausible. These are two score on extrinsic and intrinsic motivation and three self-esteem scores: general self-esteem, schooling self-esteem and work-related self-esteem.

Table 2 reports the summary statistics of these control variables and presents a comparison between zero attendances (i. e., treatment zero) and those with non-zero treatment values (0-any) and with 2 and 4 attendances (i. e., full attendance), denoted (0-2) and (0-4) respectively. Note that we do not expect these controls to be balanced over zero and non-zero treatment values. From all the controls, only French nationality, over-age delayed and repeat present significant differences between these two groups. This determines that the conditioning process is important to control for self-selection into treatment. Taken together the results indicate that the high-ability students are not particularly more likely to attend the full program. When comparing 0 and 4 attendances, all covariates are balanced.

Moreover, we compute an overlapping analysis of the propensity scores, which are required for the multi-valued discrete treatment analysis and serve as evidence of the reliability of the continuous case. Figure 5 reports the estimated kernel density estimate of the probability of a treatment value of 0 (vs. any non-zero) for observations with $T_i = 0$, 1 (vs. 0) for observations with $T_i = 1$, 2 (vs.0) for observations with $T_i = 2$, 3 (vs. 0) for observations with $T_i = 3$, and 4 (vs. 0) for observations with $T_i = 4$, all estimated from separate probit models using the set of covariates X. Table 3 presents the marginal effects of the estimated models. The graph shows that there is a large overlapping region for all values of the treatment indicator, but there is a clear differentiation between 0 and the rest.

5 Empirical results

The empirical results are reported in Figures 1-4 for CTE models and Table 4 for MTE models. Figures 1-2 correspond to the ADRF and ACTE es-timates using Hirano and Imbens (2004), our preferred estimator for CTE analysis, and Figures 34 correspond to the ADRF estimates using Flores, Flores-Lagunes, Gonzalez, and Neumann (2012) estimator, which serves as a robustness check. In all cases, the interpretation of the results depends on the comparison to 0 sessions (i. e., no attendance to any meeting), and can thus be interpreted in terms of their statistical significance and the dir-ection of the curves. The effects are measured in standard deviations of the outcome variable.

We first evaluate the program effect on academic performance, using the overall average and number of absences, which as explained above. The first two figures in Figure 1 report the estimated ADRF for each case using Hirano and Imbens (2004) estimator. All statistical analyses reveal that there is no significant difference between the control group (i. e., zero treatment that corresponds to control group and no attendance to any session) and the treatment group attending up to 2 sessions, but there is a positive effect from 3 to 4 sessions. A similar result is found in Figure 3 using Flores, Flores-Lagunes, Gonzalez, and Neumann (2012) estimator. When the same effect is analyzed through the multi-valued discrete case (Table 4), there is a positive significant effect when comparing 4 attended sessions with 0 for both grades and absences, statistically significant at 95% . As a consequence, it can be stated that the only significant effect, as compared to the control group is that of full attendance.

These positive results confirm the previous findings in the literature stating a positive effect of mentoring programs on student's performance (among the others, Campbell and Campbell (1997), Slicker and Palmer (1993), Heckman and Rubinstein (2001), Angrist, Lang, and Oreopoulos (2009), Karanja and Gikungu (2014)). Note that the mentoring program is not particularly designed to motivate students in their studies; therefore, the improved academic performance is an interesting by-product of mentoring exercises. We can speculate that job market information encourages students to put additional effort on their studies too. We will see below that even if treated students *believe less in their potential*, they still increase their effort with updated (*minor but more realistic*) beliefs. It should be noted, however, that there is no statistically significant effect on *Ambition* (ambition on continuing studying after secondary school) for any sessions.

For the outcome variable *Job research initiative*, the corresponding Figures in 1 and 3 show the estimated dose response functions. In the former case we observe an initial drop in the effect after the first session, which is reversed by 3 sessions (although the confidence interval contains zero for full attendance). Similar results can be corroborated using the MTE analysis. In this case only the 4 sessions have a significant effect as compared with no attendance. Overall, the MTE and CTE analysis reveals that there is heterogeneity across number of sessions, but there is a positive effect that only appears for a high enough number of sessions.

Regarding *Extrinsic motivation* and *Intrinsic motivation*, findings are mixed, with a negative impact of the program on extrinsic motivation for the first two sessions and on intrinsic motivation for the second and the third sessions. However, none of these results are statistically significant. In fact, for the MTE none of the differences among treatment values are significant.

The program seems to have a weak positive effect also on *General self-esteem* and *School self-esteem.* Note that for these two variables, there is an initial negative effect, which is reverted for students with full attendance. However, for *Work-related self-esteem*, the program shows negative impact. This may be explained by the fact that the more the mentees become familiar with the characteristics of the labor market they will face, the more they become aware of difficulties in pursuing possible career paths in accordance with both potential further studies after high school and desired labor market outcomes. The objective of the program was not to deflate incentives or to demotivate the students. The negative effect observed here is due to the fact that thanks to the program, the treated students start to question themselves about their current schooling choices and future plans, and to realize that a concrete plan needs to be elaborated in accordance with their own preferences, possibilities and the labor market prospects.

These effects are corroborated when looking at the multi-valued effects in a discrete manner. In particular, we observe a weak significant negative effect on the work-related self-esteem for 2 sessions. Although there may be many competing reasons for this effect, one possible explanation is that the students might be updating rationally. The literature on overconfidence suggests people often do not update rationally and are trapped in a cognitive bias in which low ability individuals have illusory superiority and mistakenly assess their cognitive ability as greater than it is. This negative effect suggests that students might have overestimated their skills, known as the Kruger-Dunning effect (Kruger and Dunning, 1999), and the mentoring program leads them to adjust their beliefs about their skills downward, hence neutralizing it. The cognitive bias of illusory superiority comes from the inability of low-ability individuals to recognize their lack of ability; without the self-awareness of meta-cognition, low-ability individuals cannot objectively evaluate their actual competence or incompetence. On the other hand, individuals with high ability incorrectly assume that tasks that are easy for them are also easy for other people. As such, our result agrees that recognizing one's own real skills and ability to perform in the job market (provided the mentoring sessions inform about that) may correct previous (unreal or undefined) self-assessments.

We acknowledge the fact that a deeper discussion around *rationality* would be necessary if more data was available. However, we suggest some evidence on the fact that students who are in the control group may be overestimating their job skills and possibilities (namely through *both* negative effects for *Job market self-esteem* in Table 4, for the comparison with 0 versus 2 and 4 sessions). Additionally, updating the beliefs for the treatment group (as shown also in Table 3 with the positive *Career choice* impact) leads to improved welfare (as shown also in Table 4 with grades, absences and *Job research initiative* variables) by avoiding systematic mistakes in terms of educational and professional choices.

The description above is corroborated when looking at *Career choice* (i. e., the mentee knows which career he/she wants to pursue or not) and *Career choice, concrete* (i. e., the mentee is able to provide examples of the career he/she wants to pursue). The program diminishes the confidence mentees had before on their expected career choice. This, again, could be explained by the fact that the more information students have about the job market characteristics, the more they both discover new careers that could be suitable for them and become aware of the challenges to pursue a potential career path in accordance with the correct studies. At a first glance, it may appear puzzling that the effect of full attendance is negative on *Career choice* and positive on *Career choice, concrete*. However, the treated students are less likely to know which career they want to pursue because they are updating their beliefs. And only when we compare both groups, *conditional on* knowing which career they want to pursue, are the treated students more likely to be able to provide examples of the career they want to pursue because they have better information on labor markets.

Finally, positive effects are registered on *Job market knowledge* starting session 1. This is supposed to be an explicit outcome of the mentoring program, and as such, it reveals that students acquired information about the job market. When looking at the multi-variate effects the only significant effect is that of 4 sessions.

5.1 Placebo tests

In order to analyze the validity of the previous results we consider the implementation of placebo tests as in Choe, Flores-Lagunes, and Lee. (2015). The main idea is to use baseline measure variables as outcomes to analyze if the procedure results are driven by the method. In particular, if we repeat the same exercises as above but using baseline level variables there should be no effect.[10]

We use the variables of motivation (extrinsic and intrinsic) and the self-esteem ones (general, school and work), which we used as control variables for the previous analysis. For these we run the continuous and multi-valued discrete treatment effects analysis. The results appear in the Appendix. In all cases there are no statistically significant effects for any values of the treatment indicators.

6 Conclusion

Beyond constrained access to credit, which constitutes a concrete impairment to continuing education, students' aspiration and level of information on the job market play a fundamental role in their decisions about their career path. For this reason, a mentoring program pairing an older or more experienced individual as a guide that provides students with more accurate information and boosts their aspiration, might have a negative effect on school dropout and positive effect on academic performance. In this

[10]We are grateful to an anonymous reviewer for pointing this.

study, we evaluate the impact of a mentoring program that provides mentors to French high schools students from underprivileged social background helping them in their academic orientation and in the drawing up of their professional project and orientation. Since we are interested in the particular heterogeneity that arises from the fact that mentoring programs vary in intensity and frequency depending on the quantity and nature of the mentoring sessions, we evaluate mentoring from a multi-valued and continuous treatment perspective, where "number of sessions attended" is the treatment. We used two empirical strategies: the average dose response function for continuous treatment and the multi-valued treatment effects models.

The statistical analysis reveals that, despite the fact that there is no significant difference between the control group (i. e., 0 meetings, control group and no attendance to any session) and the treatment group attending 2 sessions, there is a positive effect from 2 to 4 sessions on variables representing academic performance. In general, the only significant effect is that of full attendance. The overall conclusion of this study is that, if available, frequency, intensity and duration of treatment is an important factor to consider in treatment analysis.

In terms of the specific mentoring program, these results show that information about prospective labor market opportunities feeds back positively into academic performance. The program, however, has a negative effect on job self-esteem, suggesting that acquiring information on job market prospects updates students' priors on their skills and possibilities. This points out to neutralizing a potential Kruger-Dunning type cognitive bias.

This effect suggests that the program drove students to change their beliefs, abandon their certitudes and to revise their projects in a more realistic and prudent way.

Of particular interest are those cases such as *Job research initiative*, *General self-esteem* and *School self-esteem* where the initial effect is negative, but becomes positive with full attendance. For instance, in Behaghel, Chiodi, and Gurgand (2013) report, the J-PAL evaluators find that students in treatment classes were more uncertain about their plans after high school: one year after the start of the program, 31 percent of students in treatment classes did not have a defined professional plan compared to 27 percent in comparison classes. While this was regarded as an effect of low intensity of the treatment, a different effect could have been observed if the treatment was considered as continuous. In fact, the overall conclusions are in line with the main message of this paper, indicating that increasing the duration of the program to allow for the mentor-mentee relationship to develop could enhance the impact of similar mentoring programs.

As noted by an anonymous referee, if more data were available, these analyses can be used to discuss the optimal dosage. The results here suggest that full attendance is required for obtaining the positive expected effects, and in fact, those that do not complete the full program, might end up with negative outcomes.

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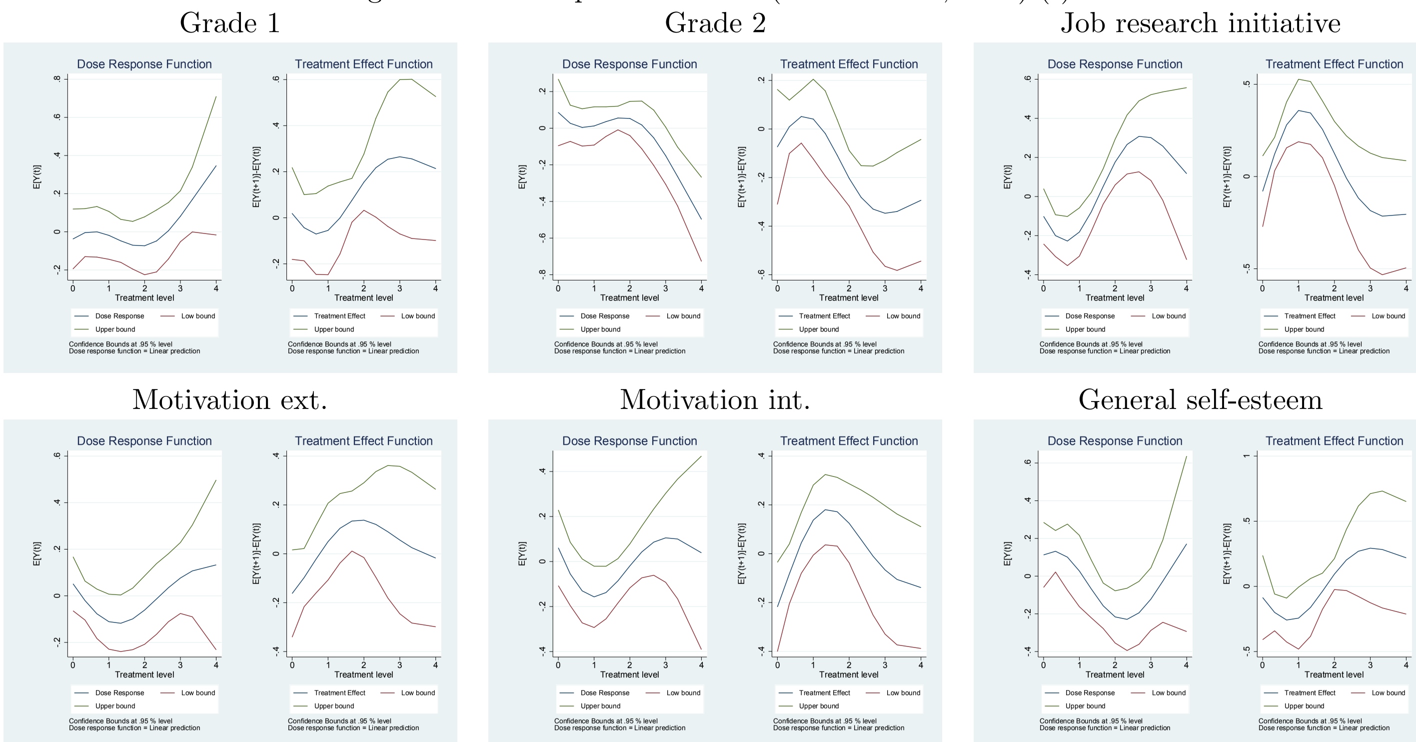
Figure 1: Dose response function (Hirano et al., 2004) (I)

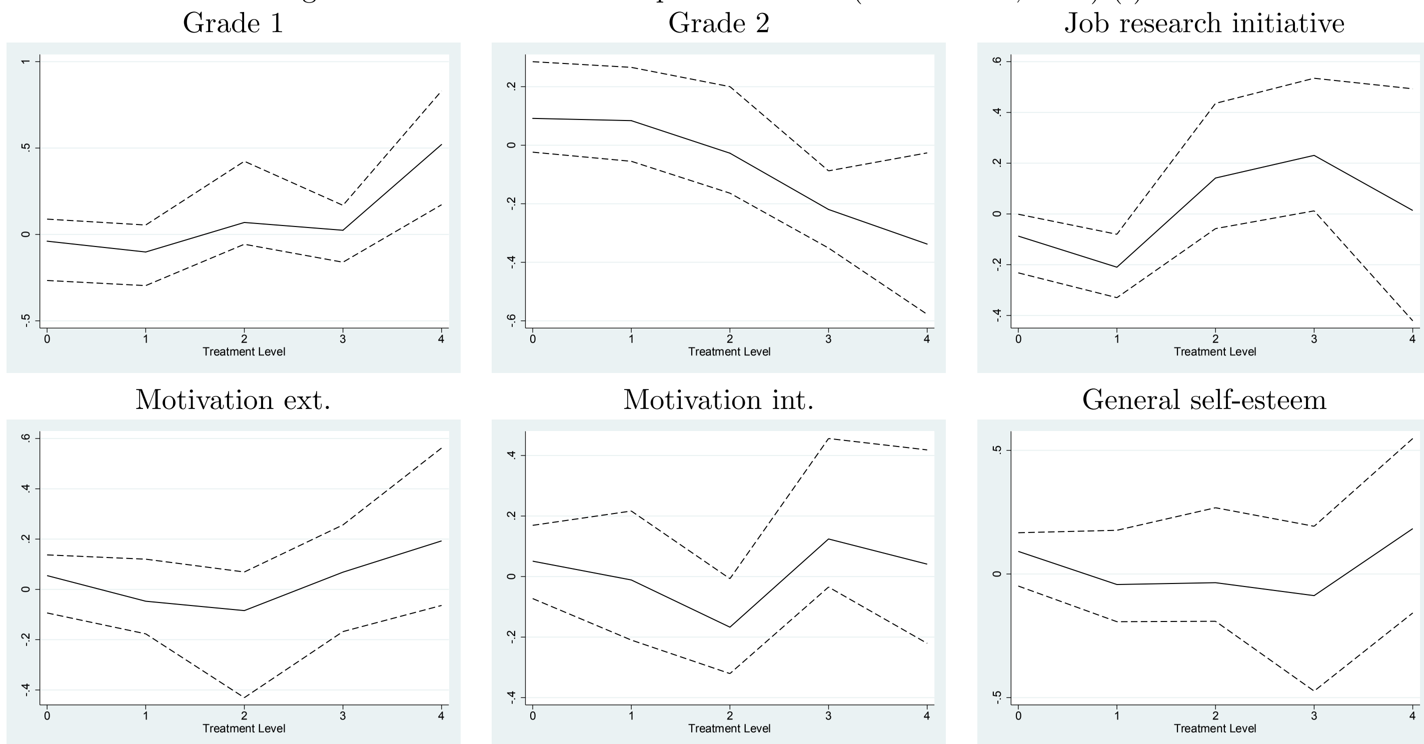


Notes: The right figure is the ADRF estimate and the left figure is the ACTE estimate using Hirano et al. (2004) estimator. 95% confidence intervals are computed.

Figure 2: Dose response function (Hirano et al., 2004) (II)

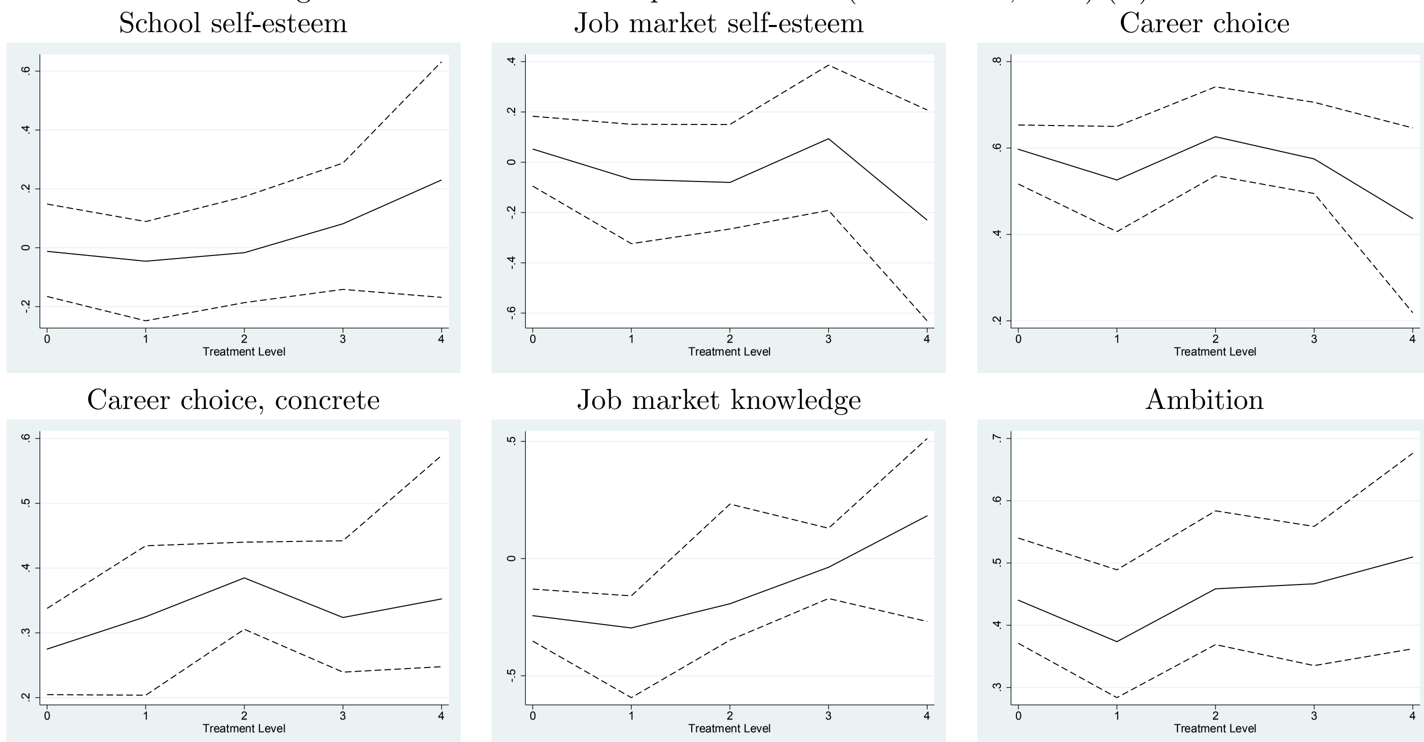
Notes: The right figure is the ADRF estimate and the left figure is the ACTE estimate using Hirano et al. (2004) estimator. 95% confidence intervals are computed.

Figure 3: Alternative dose response function (Flores et al., 2012) (I)



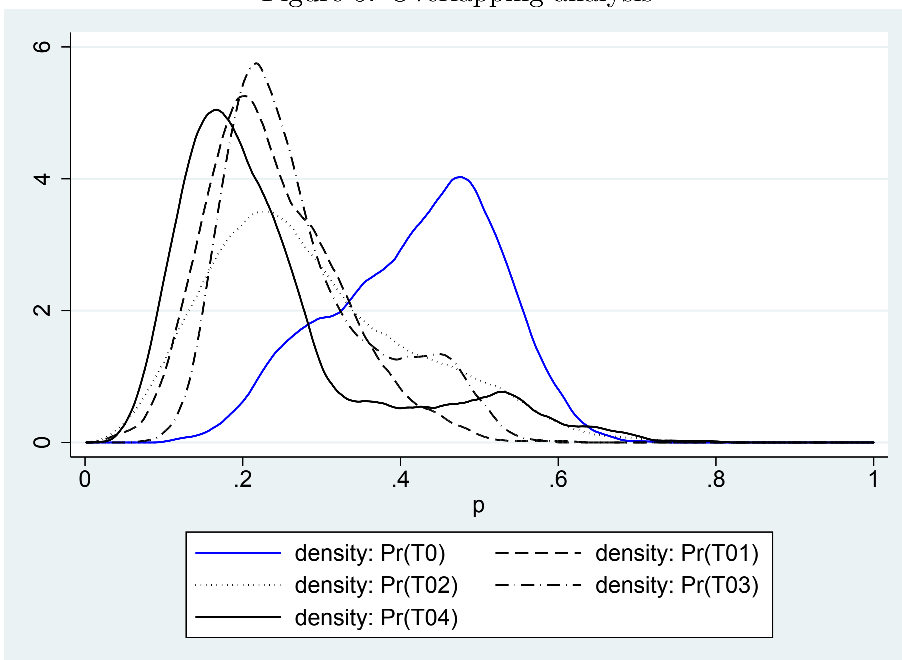
Notes: The figure is the ADRF estimate using Flores et al. (2012) estimator. 95% confidence intervals are computed.

Figure 4: Alternative dose response function (Flores et al., 2012) (II)



Notes: The figure is the ADRF estimate using Flores et al. (2012) estimator. 95% confidence intervals are computed.

Figure 5: Overlapping analysis



Notes: Pr[T0]: predicted probability of treatment = 0 vs > 0 for those observations with $T_i = 0$; Pr[T01]: predicted probability of treatment = 1 vs = 0 for those observations with $T_i = 1$; Pr[T02]: predicted probability of treatment = 2 vs = 0 for those observations with $T_i = 2$; Pr[T03]: predicted probability of treatment = 3 vs = 0 for those observations with $T_i = 3$; Pr[T04]: predicted probability of treatment = 4 vs = 0 for those observations with $T_i = 4$.

Table 1: Treatment variable

	Continuous			Discrete		
Treatment	Obs.	Percent	Cum.	Obs.	Percent	Cum.
0	267	41.98	41.98	267	41.98	41.98
1/3	2	0.31	42.30			
2/3	1	0.16	42.45			
1	81	12.74	69	83	13.05	55.03
4/3	47	7.39	62.58			
5/3	14	2.20	64.78			
2	55	8.65	73.43	103	16.19	71.23
7/3	43	6.76	80.19			
8/3	22	3.46	83.65			
3	40	6.29	89.94	97	15.25	86.48
10/3	37	5.82	95.75			
11/3	-					
4	27	4.25	100.00	86	13.52	100.00
Total	636	100.00		636	100.00	

Table 2: Control variables summary statistics

Control	Mean	Std.dev.	Min	Max	(0-any)	p-val	(0-2)	p-val	(0-4)	p-val
Math	9.38	3.58	0	19.5	0.468	0.104	0.165	0.762	-0.263	0.666
French	8.97	3.52	0	16.3	0.278	0.325	-0.258	0.626	-0.433	0.548
Parents white-collar	0.307	0.461	0	1	0.020	0.587	0 .009	0.893	0.059	0.519
Parents non-labor force	0.126	0.337	0	1	0.012	0.563	0.043	0.325	0.024	0.718
Sex	0.481	0.500	0	1	0.003	0.931	0 .119	0.102	-0.072	0.484
French nationality	0.857	0.350	0	1	0.072	0.008	0 .08	0.151	0.047	0.519
Over-age delayed	0.208	0.016	0	1	-0.105	0.000	-0.095	0.197	-0.002	0.977
Repeat	0.207	0.406	0	1	-0.106	0.001	-0.072	0.235	0.075	0.939
Motivation (extrinsic)	45.0	0.33	44.4	45.7	-0.563	0.410	0.199	0.876	0.597	0.692
Motivation (intrinsic)	30.9	0.36	30.1	31.6	-0.238	0.753	0.392	0.760	-1.281	0.486
Self-esteem (general)	15.3	0.18	14.9	15.6	0.377	0.284	0.564	0.348	-0.084	0.931
Self-esteem (school)	12.4	0.13	12.3	12.8	0.410	0.117	0.696	0.148	-0.251	0.734
Self-esteem (work)	6.44	0.067	6.31	6.58	-0.238	0.100	-0.166	0.479	-0.323	0.351

Notes: The number of observations is 636. (0-any) presents the mean difference from a t-test for each covariate between 0 attendances and any non-zero attendance. (0-2) shows the mean difference between 0 attendances and half attendance (2 sessions). (0-4) shows the mean difference between 0 attendances and full attendance (4 sessions).

Table 3: Selected probit models

VARIABLES	(0)	(1)	(2)	(3)	(4)
Math	0.0054	-0.0114*	-0.0107	0.0031	0.0013
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
French	0.0031	-0.0003	0.0103	-0.0028	-0.0130*
	(0.006)	(0.007)	(0.008)	(0.007)	(0.007)
Parents white-collar	0.0054	0.0306	-0.0145	0.0042	-0.0100
	(0.045)	(0.053)	(0.055)	(0.053)	(0.053)
Parents non-labor force	0.0611	-0.0163	-0.0756	-0.0360	-0.0232
	(0.063)	(0.069)	(0.066)	(0.068)	(0.069)
Sex	0.0008	0.0596	-0.0466	-0.0253	0.0120
	(0.043)	(0.050)	(0.051)	(0.049)	(0.050)
French nationality	0.1229**	0.0960	-0.1366*	0.0125	-0.3042***
	(0.055)	(0.066)	(0.079)	(0.076)	(0.073)
Over-aged delayed	-0.0656	0.0040	0.0666	0.0899	0.0383
	(0.050)	(0.059)	(0.062)	(0.061)	(0.060)
Repeat	-0.1112*	0.1179	0.1274	0.1210	0.0331
	(0.058)	(0.083)	(0.080)	(0.079)	(0.076)
Motivation (extrinsic)	-0.0012	0.0022	0.0007	0.0018	-0.0005
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Motivation (intrinsic)	0.0008	-0.0025	-0.0013	0.0004	0.0015
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Self-esteem (general)	0.0074	-0.0077	-0.0024	-0.0024	-0.0110*
	(0.005)	(0.006)	(0.007)	(0.007)	(0.006)
Self-esteem (school)	0.0050	0.0004	-0.0111	-0.0023	-0.0034
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Self-esteem (work)	-0.0243**	0.0099	0.0272*	0.0166	0.0171
	(0.012)	(0.014)	(0.015)	(0.015)	(0.014)
Observations	636	350	370	364	353
Model	T=0 vs. >0	T=1 vs. 0	T=2 vs. 0	T=3 vs. 0	T=4 vs. 0

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Marginal effects on the probability of success, defined as (0) 0, (1) 1, (2) 2, (3) 3, (4) 4.

Table 4: Impact of the mentoring program using multivalued discrete treatment effects

Discrete value	Coef.	Std.error	p-value
Overall grade			
(1 vs 0)	0.139	0.115	0.229
(2 vs 0)	0.275	0.101	0.007
(3 vs 0)	0.121	0.106	0.256
(4 vs 0)	0.237	0.098	0.015
Obs.		513	
Absences			
(1 vs 0)	-0.100	0.115	0.387
(2 vs 0)	-0.088	0.107	0.414
(3 vs 0)	-0.285	0.101	0.005
(4 vs 0)	-0.319	0.107	0.003
Obs.		636	
Job research initiative			
(1 vs 0)	-0.169	0.082	0.039
(2 vs 0)	0.060	0.111	0.591
(3 vs 0)	0.219	0.135	0.103
(4 vs 0)	0.448	0.170	0.008
Obs.		575	
Extrinsic motivation			
(1 vs 0)	0.011	0.121	0.928
(2 vs 0)	-0.068	0.117	0.558
(3 vs 0)	-0.031	0.136	0.822
(4 vs 0)	-0.014	0.102	0.891
Obs.		516	
Intrinsic motivation			
(1 vs 0)	0.145	0.099	0.143
(2 vs 0)	0.032	0.120	0.792
(3 vs 0)	-0.049	0.102	0.630
(4 vs 0)	0.192	0.100	0.848
Obs.		513	

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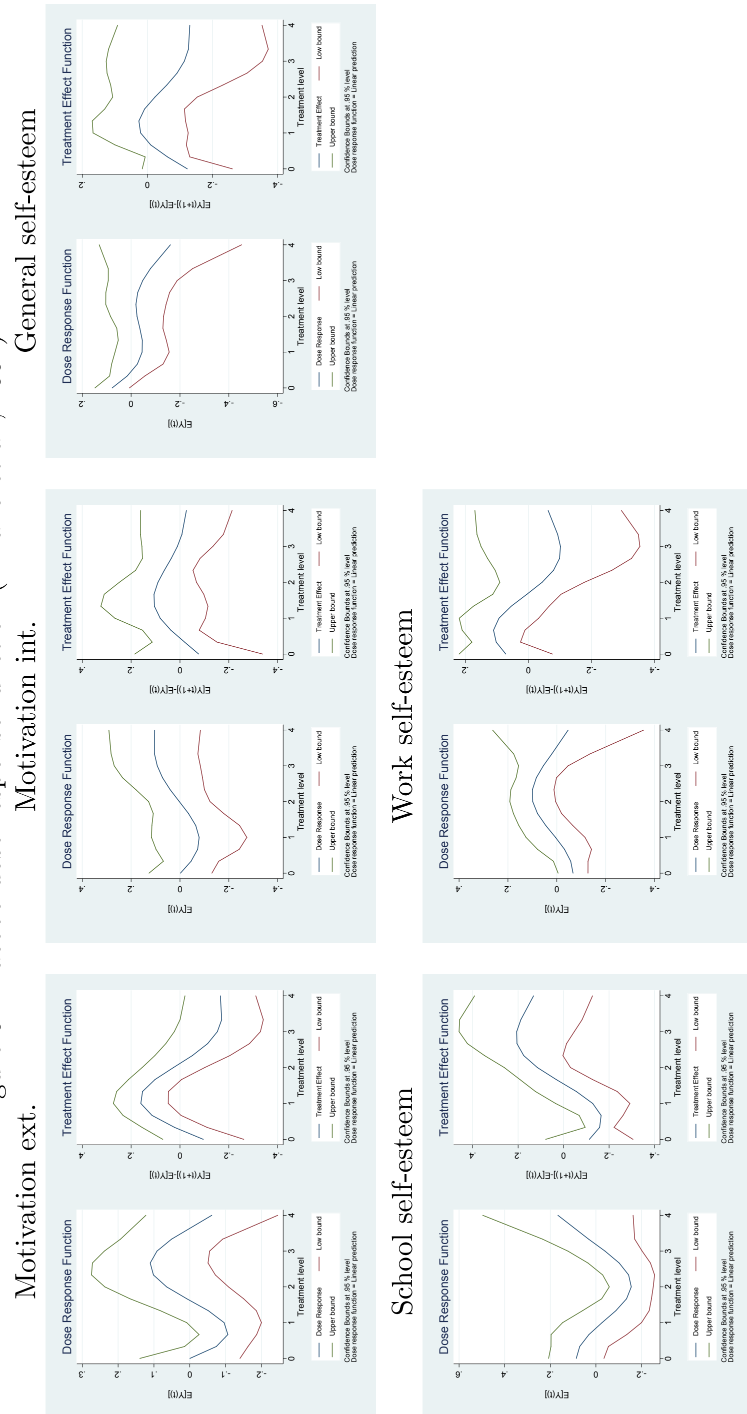
Discrete value	**Coef.**	**Std.error**	**p-value**
General self-esteem			
(1 vs 0)	-0.052	0.121	0.665
(2 vs 0)	-0.148	0.115	0.198
(3 vs 0)	-0.089	0.128	0.483
(4 vs 0)	-0.118	0.112	0.290
Obs.		523	
School self-esteem			
(1 vs 0)	-0.015	0.136	0.910
(2 vs 0)	-0.73	0.129	0.570
(3 vs 0)	0.100	0.139	0.475
(4 vs 0)	0.228	0.132	0.084
Obs.		522	
Work-related self-esteem			
(1 vs 0)	-0.077	0.137	0.574
(2 vs 0)	-0.242	0.129	0.061
(3 vs 0)	0.101	0.127	0.426
(4 vs 0)	-0.198	0.136	0.145
Obs.		518	
Career choice			
(1 vs 0)	-0.083	0.070	0.236
(2 vs 0)	-0.014	0.062	0.821
(3 vs 0)	-0.018	0.066	0.785
(4 vs 0)	-0.145	0.061	0.017
Obs.		575	
Career choice. concrete			
(1 vs 0)	0.002	0.063	0.975
(2 vs 0)	0.081	0.067	0.227
(3 vs 0)	0.092	0.062	0.138
(4 vs 0)	0.118	0.061	0.053
Obs.		575	
Job market knowledge			
(1 vs 0)	-0.151	0.162	0.349
(2 vs 0)	0.025	0.136	0.853
(3 vs 0)	0.064	0.123	0.600
(4 vs 0)	0.393	0.117	0.001
Obs.		575	
Ambition			
(1 vs 0)	-0.021	0.073	0.774
(2 vs 0)	0.033	0.064	0.606
(3 vs 0)	0.002	0.060	0.973
(4 vs 0)	0.073	0.061	0.231
Obs.		575	

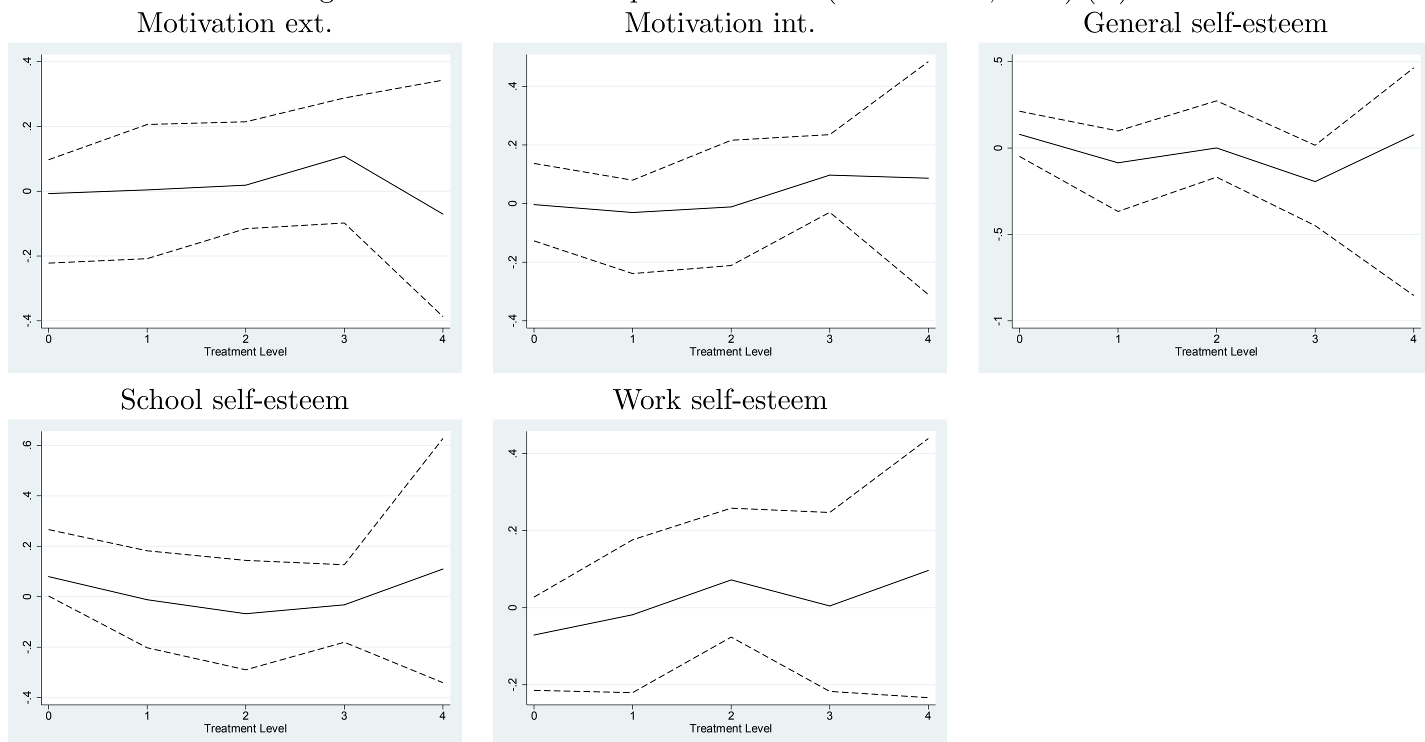
Appendix

Figure 6: Placebo dose response function (Hirano et al., 2004)



Notes: The right figure is the ADRF estimate and the left figure is the ACTE estimate using Hirano et al. (2004) estimator. 95% confidence intervals are computed.

Figure 7: Placebo dose response function (Flores et al., 2012) (II)



Notes: The figure is the ADRF estimate using Flores et al. (2012) estimator. 95% confidence intervals are computed.

Table 5: Placebo impact of the mentoring program using multivalued discrete treatment effects

Discrete value	Coef.	Std.error	p-value
Extrinsic motivation			
(1 vs 0)	0.063	0.127	0.618
(2 vs 0)	0.033	0.112	0.5767
(3 vs 0)	0.135	0.121	0.261
(4 vs 0)	0.098	0.1124	0.429
Obs.		636	
Intrinsic motivation			
(1 vs 0)	-0.002	0.123	0.984
(2 vs 0)	-0.035	0.106	0.738
(3 vs 0)	0.123	0.119	0.300
(4 vs 0)	0.094	0.125	0.455
Obs.		636	
General self-esteem			
(1 vs 0)	-0.108	0.116	0.353
(2 vs 0)	-0.010	0.103	0.922
(3 vs 0)	-0.004	0.1118	0.974
(4 vs 0)	-0.188	0.133	0.156
Obs.		636	
School self-esteem			
(1 vs 0)	-0.067	0.131	0.605
(2 vs 0)	-0.162	0.129	0.124
(3 vs 0)	-0.031	0.139	0.806
(4 vs 0)	-0.103	0.132	0.441
Obs.		636	
Work-related self-esteem			
(1 vs 0)	0.004	0.135	0.978
(2 vs 0)	0.194	0.112	0.085
(3 vs 0)	0.161	0.121	0.182
(4 vs 0)	0.133	0.125	0.286
Obs.		636	

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