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Nudging communication for students at risk: experimental evidence from an Italian university

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Abstract
To address the dropout issue in an Italian university, this research deals with stimulating at-risk students to enroll in tutoring services. Students with a predicted dropout risk are assigned to different nudging communication treatments via email through a rigorous randomized controlled trial. Findings highlight that messages based on a "social comparison" nudge obtains positive and statistically significant effects to increase students' propensity towards attending tutoring services.

Keywords
Informative nudges, Students at risk of drop-out, Randomized Controlled Trial, Regression Discontinuity Design

JEL codes
I23 Higher Education • Research Institutions

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1. Introduction, motivation and research questions

A robust body of academic research confirms the importance of reducing dropout rates, i.e., the percentage of early leavers in the education system. In Italy, the situation is particularly worrying, with a university dropout mean rate of around 15% between the first and second year, which increases until 25% within the fourth year, according to the National Agency for the Evaluation of the University and Research. The consequences of this phenomenon are serious. For example, individuals who early leave higher education have a higher probability of being unemployed or having unstable careers (Rumberger and Lamb, 2003; Schnepf, 2017).

Detecting students at-risk of dropping out as early as possible will give institutions the opportunity of setting out remedial interventions, with large potential benefits in the long run. The emerging use of Early Warning Systems (hereafter, EWS) in the educational domain (Macfadyen and Dawson, 2010) holds the promise to improve the fight against dropout rates[1]. As part of a data analytics process, EWS provides powerful and timely insights to the decision-makers, for taking their decisions in a more informed and timely way. For example, identifying students at-risk early in time allows to organize remedial education programs to help them with more difficult courses and exams. The prediction of students' performance represents the input for institutions to set clearer objectives regarding learning outcomes (Heppen and Therriault, 2008), as well as discussing practical strategies and interventions for reducing the risk of dropout. Indeed, EWS consists of a sequential two-step set of procedures and instruments for (i) early detection of students at risk of dropping out, which can be used in turn for (ii) implementing appropriate interventions to help them stay in Education. In relation to the former goal, empirical academic papers increasingly define and estimate dropout rates with ever-increasing precision, also examining the factors associated with dropout of individual students (Seidel and Kutieleh 2017; Korhonen and Rautopuro 2019; Sothan 2019; Cannistrà et al., 2022; Von Hippel and Hofflinger, 2021).

However, simply identifying at-risk students does not alleviate the risk that these students face. Indeed, to make EWS effective in preventing students from dropping out and meeting major educational milestones, educational institutions must tailor interventions based on early warning indicators (Jokhan, Sharma, and Singh, 2019; Raffaghelli et al., 2022).

These two research streams can be conceived as sequential: the outputs obtained with the prediction of dropouts serve as the key input when setting remedial interventions. This is the approach adopted in this paper, that describes the use of an EWS in a public Italian university. After having estimated the dropout probabilities for first-year students (through a method developed by Cannistrà et al. in 2022), a nudging intervention (based on information towards students at-risk) is implemented and evaluated. The information provided to the students deals with the possibility to attend a free-of-charge tutoring service offered by the University. The choice of outreaching students towards tutoring is motivated by the fact that previous literature suggests

[1] In this paper, we focus on the use of EWS for higher education, although similar approaches are applied in the context of k-12 education (see Bowers, 2021).

that traditional remedial intervention, such as tutoring, is effective in improving students' academic career (Arco-Tirado, Fernández-Martín, and Hervás-Torres, 2020; Bettinger and Baker, 2014; Kot, 2014). Despite the literature focused on the effectiveness of tutoring programs, less is known about the levers for student outreach to promote actions that could save their academic careers. In this paper, nudging communication is adopted to gently push predicted at-risk students into joining the tutoring services offered for free by the university during the second semester.

An experimental setting is organized at Politecnico di Milano (PoliMi), the Italian most prestigious public university according to international rankings (98^{th} in the QS World Ranking), offering degree programs in Engineering (focus of this research work), Architecture and Design. The experiment takes place in the 2021/22 academic year, following a pilot in 2020/21. After having randomized first-year Engineering students with an associated dropout risk and assigned them to treatment or control groups, the effect of nudging and communication is rigorously evaluated by means of a Randomized Controlled Trial (RCT). The innovation of this paper relies on a double treatment: two different types of messages are adopted, which are based on different theoretical frameworks – namely, "social comparison" and "returns to schooling", while the control group receives a standard message that just reminds them the possibility of tutoring freely offered by the university during the second semester. Thanks to randomization, the experiment lays robust foundations in exploring the causal nexus between treatments (differentiated nudging communication) and outcome of interest (tutoring enrollment). We answer the following, specific research question: do different messages have a different impact on students' propensity to enroll to a tutoring service?

A specific focus of this research work relies on contributing to the emerging academic strand about the evaluation of nudging communication in education. Despite the increasing research on behavioral economics and, specifically, nudging strategies to improve academic outcomes, there is comparatively little empirical evidence on the characteristics of specific, differentiated and effective nudges (Castleman et al., 2021).

The remainder of this paper is organized as follows. Section 2 presents the main features of the academic literature about evaluation of nudging interventions in educational settings. Section 3 describes the analytical strategy. Sections 4 and 5 illustrate main findings and conclusive remarks of this work.

2. Related literature – nudging approaches in Higher Education

This paper aims at shedding new lights on the potential effects of nudging-based interventions in the Higher Education (HE) setting. In this vein, the literature we are looking at is not dealing with the effectiveness of tutoring services (not evaluated here) – interested readers can refer to Hardt et al., (2023) and De Cort & De Witte (2025). In this section, we instead review the studies that assess the effect of nudging interventions in HE through robust and causal methods.

In HE, it is often assumed that students are sufficiently self-motivated to keep the pace with their academic career. However, retention rates and the dropout phenomenon show that such assumption is not always verified (Contini, Cugnata, and Scagni, 2018; Von Hippel and Hofflinger, 2021). A recent field of literature focuses on evaluating the use of nudging communication to “gently push [students’] behaviors in the desired direction” (Damgaard and Nielsen, 2018). This section provides an overview of the main results of nudging communication in HE presented in academic literature. Nudging interventions show mixed results regarding their effects on students. Results’ heterogeneity may be due to the different types of nudging, the communication sender, or the final goal of the intervention. A systematic summary of the existing evidence based on rigorous causal studies is reported in Table A1, in the Annex A. It is worth noting that almost all the existing studies refer to experiments held in US, and the focus on an Italian case is a specific novelty of this paper.

Castleman and Page (2015) evaluate the effect of an automated and personalized text messaging campaign to remind college-intending students of required pre-matriculation tasks and to connect with counselor-based support. The intervention substantially increases college enrollment among students by just providing them useful information. To the same end, Castleman and Page (2016) investigate the impact of a personalized text messaging intervention designed to encourage college freshmen to send their Free Application for Federal Student Aid (FASFA) and maintain their financial aid for the next academic year. The messages contain information about where to get help with applications for financial aid, important aid-related deadlines and requirements, and offered students assistance on key steps of the financial aid request process. The financial aid text message campaign has large and positive effects on the continued college persistence of first-year students at community colleges.

To deepen the investigation about nudging communication targeted to low-income students, Castleman and Meyer (2020) send simplified information, encouragement, and access to one-on-one advising programs. Results suggest that students participating in the texting campaign complete more freshman year formative credits, compared with similar students who did not have the opportunity to sign up for the text campaign, even if these effects are not always statistically significant.

Gurantz et al. (2020) examine whether Virtual Advising, a project of college counseling using technology to communicate remotely, increases post-secondary enrollment in selective colleges. Findings show mixed results: the virtual advising offer has no impact on overall college enrollment, but it increases enrollment in high graduation colleges. No significant effects are found by Bird et al. (2021) in scaling up the text messaging campaign to remind students to enroll in college. The discussion about the possibility and the effectiveness of scaling up nudging interventions is also deepened by Avery et al. (2021). The authors investigate the efficacy of two text messaging campaigns to remind students about and support them with key steps in enrolling in college. The goal of the text-based interventions is to increase the college entrant rate. The study sets two different experiments. The first one involves a US national sample of students who were sent messages, approximately once per month, from counselors of an external company. The second treatment involves a set of schools in Texas, with students receiving personalized messaging from high school counselors, once a week or once a fortnight. Overall, results show that both treatments obtain positive but minor effects in the national sample, while significant improvements are obtained in college enrollments for a subset of students in the Texas schools involved in the study. This finding might represent an input for reflecting on the message sender, the population's size, and the frequency of communication.

A further piece on this literature is added by Castleman and Page (2017). The authors experimentally investigate whether providing (i) only students or (ii) both students and their parents personalized communication about the tasks that students need to complete to enroll in college leads to an increased on-time college enrollment compared to providing communication to students only. Indeed, previous research on school-to-parent communication shows improvement in students' outcomes (Bergman, 2020). However, despite the study finds significant increase in the number of on-time college enrollments after nudging intervention on students, texting both parents and students do not increase the efficacy of the outreach.

Our paper innovates existing research with three main contributions. First, it adopts the output of a Machine Learning (ML) dropout prediction algorithm as input for reaching the most at-risk students. To the best of our knowledge, this represents the first attempt to combine data analytics and nudging interventions in the HE domain (in the real spirit of an EWS). Second, the use of two nudging leverages allows to compare the effects of the intervention assessing the specific differences in nudging mechanisms. Third, the experiment presented in this paper has been implemented in a European university, a setting rarely found in nudging-related academic literature, which is almost completely US-based.

3. Methodological approach

The experiment relies on different phases, detailed in this section. The key features of this work are the selection of highly at-risk students made by predictive models, a two-phase experiment (pilot and RCT) and, in the main evaluation, the testing of two alternative nudging messages for reaching out to at-risk students about tutoring activities.

The dropout predictions serve as input to select the population of interest (first-year at-risk students). The pilot project, organized in 2020/21, evaluates the effect of a standard communication about the possibility to enroll to tutoring programs only for highly at-risk students. The main evaluation, held one year later, targets all the predicted dropout students and it evaluates the effects of two alternative nudging messages with the same goal of convincing them to enroll to tutoring activities provided for free by the university. In this case, the evaluation relies on the random assignment of at-risk students to one of the messages. Figure A1 in the Annex A presents the main phases of the preliminary and the main experiments. The next paragraphs will deepen the main characteristics of this work: the Machine Learning predictions (3.1.), the evidence from the pilot experiment (3.2.), the design (3.3.), the identification strategy (3.4.) and the data (3.5.) adopted in the RCT evaluation.

3.1 Prediction of at-risk students

One of the main innovations of this paper is the use of dropout predictions obtained using statistical models and ML algorithms to identify at-risk students to target them with a nudging-based intervention. To this end, we follow the algorithms presented in Cannistrà et al. (2022). The analysis includes all first-year students of Engineering courses at PoliMi between 2010 and 2017. The models are run adopting a set of student-level covariates, extracted from the administrative database. This set of information describes students' family and background characteristics (i.e., socio-economic status, gender, age, residency, citizenship), previous academic results (i.e., high school's track and final grade) and academic information at the end of their first semester (i.e., PoliMi admission test score, formative credits and grades at the end of the first semester, type of degree program). The complete list and description of the variables used for prediction are reported in Annex A, Table A2. Using these students' data extracted at the end of their first semester of the first year, we predict their dropout probability by means of a generalized linear mixed-effects model and a novel generalized mixed-effects random forest (Pellagatti et al., 2021), belonging to the family of ML algorithms. This method, which considers the hierarchical structure of the data – students nested into degree programs – produces the best predictive accuracy with a training-testing approach (see Cannistrà et al. 2022 for details). The models can rely on robust estimations, computed after just one semester from the students' enrollment at PoliMi. These predictions can correctly identify more than 95% of actual dropouts at the end of the first semester of the first year. It is important to note that the formative credits obtained by students during their first semester represent the main factor that determines the prediction. Given this evidence, tutoring activities may represent a potential effective way for students' careers remediation, during the early stage at their academic journey in PoliMi, i.e. in the middle of their first year.

3.2 Evidence from the pilot study

The pilot research was organized during the A.Y. 2020/21. Based on the predicted dropout probabilities measured at the end of first semester, first-year students with an estimated probability of dropout greater than 90% received a nudging communication via e-mail from the university at the beginning of the second semester. The goal was to foster their enrollment in tutoring activities offered for free (i.e., zero fee) by the university during the spring semester to all students. Such courses were accessible online in synchronous mode (we should remember here that it was still COVID times). The focus of this preliminary research was twofold: first, to evaluate the effect of attending tutoring services on student careers, and second, to evaluate the effect of receiving the message with the advice of attending the tutoring. The analysis reported in Annex B (Table B1), conducted by means of Propensity Score Matching, suggests that attending tutoring services is effective in improving the academic career of at-risk students. Nonetheless, the results of the pilot research that evaluated the effect of the message employing a Regression Discontinuity Design showed no effect of the message in convincing students to enroll in tutoring activities (see Annex C). In the light of this evidence, one year later, during the second semester of A.Y. 2021/22, we decided to implement a second experiment testing different types of nudges in communication, with the aim of understanding potential different effects due to a different formulation of the messages. For this purpose, we organize a rigorous Randomized Control Trial (RCT).

3.3 The Experimental Design for testing the effectiveness of nudging communication

The goal of this intervention is to convince students with an estimated dropout risk to enroll in tutoring activities. The message used in the new experiment is diversified: in addition to a standard message (used as the control), we test two different nudging leverages based on two concepts, "social comparison" and "returns to schooling", inspired by Damgaard and Nielsen (2018) to evaluate their effectiveness in fostering student enrolment in tutoring services.

In this experiment, the target population does not include only students with a predicted dropout probability greater than 0.9, but it is more inclusive, involving all students. The evidence from the pilot research (Section 3.2.) suggested that students with a predicted dropout probability greater than 0.9 are very unlikely to be retained (most likely, they have already decided to dropout, and behave accordingly), so we decided to exclude them. The final sample involves 2000 students: all first-year enrolled with a predicted dropout risk higher that 25% and lower than 90%.

The experimental design relies on a randomization of the predicted dropout students, who are stratified based on their specific level of dropout probability. Students are then randomly assigned to one of the three groups: (i) control group, (ii) Social Comparison (SC) treatment, and (iii) Returns to Schooling (RtS) treatment. These two nudges represent special cases of the broad concept of informational nudges (Thaler and Sunstein, 2009; Damgaard and Nielsen, 2018). On one side, SC nudges provide information about how peers behave, facilitating the adherence to the social norms and related pressure (Coffman, Featherstone, and Kessler, 2017). Moreover, the message aims at highlighting the effectiveness of the tutoring intervention on a group of 'similar' students. This choice builds on literature results showing how the effectiveness of normative communication increases with the 'closeness of situation' of the receiver with that of the group whose behavior the message is referring to (Goldstein et al., 2008). On the other side, the RtS approach informs students about the long-run benefits associated to their educational career, after initially acknowledging the immediate personal costs related with effort (McGuigan, McNally, and Wyness, 2016). This message targets the issue of time preference and intertemporal decisions; indeed, it aims at stressing the fact that there will be future benefits to the currently required sacrifices, that is, a temporally delayed gratification. The exact texts of the two different messages are reported in Annex D, together with the baseline (traditional) text of the message.

The message is sent to the students at the end of the first semester of the first year by PoliMi administrative offices through personalized emails. The choice regarding the sender of the message builds on the assumption that an expert source, in our case the University as an institution, seems to be more effective and less intrusive for students than alternative modes, like a direct message from professors.

The target population of students is selected based on students' dropout probability, which is mainly driven by the number of formative credits the student obtains at the end of his/her first semester: the lower the credits obtained at the end of first semester, the higher the dropout probability (Cannistrà et al., 2022). We assume that the dropout phenomenon is mainly due to a lack in academic preparation, which can be addressed by tutoring services. Academic difficulties may be also related to underlying psychological and social factors which are more challenging to address and go beyond the goal of this paper. We limit the scope of this study to understand how to provide incentives to students for investing time in their academic preparation. The remedial initiative concerns the possibility, for all students, to freely enroll in tutoring activities held by doctoral students on the most challenging subjects of the Engineering Bachelor's program (such as Mathematics, Physics, Computer Science, etc.). There is neither attendance obligation, nor any formal assessment at the end of it. Given the calendar of the courses, the student may decide to follow one or more tutoring activities. Actual attendance of the tutoring services is tracked by means of a dedicated App – although we are not using this information in the paper. In other words, we are not exploring whether actual attendance of tutoring services is effective for academic performance; instead, we limit ourselves to observing whether students enroll to the tutoring service or not.

3.4 Identification Strategy

A specific feature of this paper is the random assignment of predicted dropout students to control or treatment groups. We can rely on robust estimations given the adoption of a Randomized Controlled Trial with multiple treatments. Another important consideration is that Intention to Treat and Treatment on the Treated overlaps: students cannot choose whether to accomplish or not the treatment, since the treatment is the receipt of the email with the nudging communication. However, we cannot track how students behave once they receive the communication (for example, if they open the email, or read it).

The evaluation controls for a set of individual controls stored in the PoliMi's administrative database, like demographic characteristics (i.e., gender, residency, and family income) and previous studies information (i.e., PoliMi admission test[2], high school track and grade). We adopt

[2] The University organizes admission tests about mathematics, physics, logics and text comprehension to access its programs. Students may sustain it during the last or second-last year of high school. They also have the possibility to retake the test multiple times if they fail. To be admitted to PoliMi programs, students were required to successfully pass the admission test with at least 60 points over 100, at the time of this experiment – indeed, admission rules change over time.

a linear logistic regression model to capture the treatment effect of the reception of the nudging message on the probability to enroll in tutoring activities, adjusting for the other student characteristics. The student enrollment in tutoring activities, described by the dummy variable *Tutoring (2sem) 2021/22* (1 if the student enrolls, 0 otherwise), is the outcome of interest. As mentioned above, the presence of students at tutoring activities is registered with a specific web tool that records when and which courses the student attends. For each student i, we assume *Tutoring (2sem) 2021/22* $\sim Be(p_i)$ where p_i represents the probability that student i enrolls in tutoring activities during the second semester of Academic Year (A.Y.) 2021/22. The model takes the following form:

$$\log\left(\frac{p_i}{1 - p_i}\right) = \beta_0 + \boldsymbol{\beta}_1 \times \boldsymbol{x}_i + \beta_2 \times TreatSC_i + \beta_3 \times TreatRtS_i \qquad i = 1, \dots, N$$

where $\boldsymbol{x}_i$ is the student-level vector of covariates, $\boldsymbol{\beta}_1$ is the vector of relative coefficients, $TreatSC_i$ and $TreatRtS_i$ are the dummies for the treatment assignment to SC and RtS, respectively, and β_2 and β_3 are their coefficients. The reference category is the control group. The coefficients of interest are the ones associated to the treatment effects: β_2 and β_3. To support the interpretation of results, in the subsequent analysis the odds ratios and the marginal effects are shown, together with the coefficients. The odds calculate the ratio of the probability that the event of interest (tutoring enrollment) occurs vs. the probability that it does not, while marginal effects show the change in probability when the controlling variable (the treatment) changes its value.

3.5 Descriptive statistics

The target population for this study is represented by all freshmen students (i.e., students enrolled in their first year during the A.Y. 2021/2022) for whom we estimate the associated dropout risk. Table 1 reports the summary statistics for the observed characteristics (details Table A1 in Annex A) of sample considered in the evaluation: 2,000 predicted dropout students (27.62% of total enrollments). The dropout probabilities, as well as the other students' characteristics, are balanced across the three groups, since the randomization was stratified according to them. The high p-values for the statistical comparison tests among the characteristics of the individuals in the different groups reported in last column of Table 1 confirm the success of the randomization. Regarding the sample characteristics, first-year at-risk students are mainly male (greater than 80% of the sample) and commuters (greater than 60%); commuting students are those who live outside Milan, travelling to the city every day for attending courses. Table 1 shows an average final high school grade of around 76/100 and a prevalence of a general scientific track (67% of students). In the Italian Education System, high school tracks can be general, technical or vocational. In particular, the general track, that usually (but it is not mandatory) anticipates the university, has different specializations: scientific, classical, artistic, linguistic, or social sciences. The family socioeconomic background is here approximated with the university fee paid by the student which is stratified by family income (we do not have access to income levels directly), where the highest bracket identifies students from wealthier families. Most students belong to the highest bracket, followed by the study grant group; students eligible for study grants are those with low socio-economic status and high academic performance, measured by means of Grade Points Average (GPA), where the grades are assigned by the professors. Lastly, the information about whether the student enrolls in tutoring activities during the first semester is provided: in the sample considered, the 20.4% of the students follows tutoring activities during the first semester.

[Table 1] around here

4. Main findings: the evaluation of nudging interventions

The core findings of this paper are presented in Table 2, where the effect of the differentiated nudging messages is evaluated by means of logistic regression. The evaluation is computed by sequentially adding a set of controls, from none to the whole set. The only variable evaluated separately is the *dropout_prob* because its computation is obtained from the rest of the covariates. Interestingly, the effect on stimulating students' enrolment to the tutoring service is positive and significant only for the nudging communication using SC as leverage for all the five models (with an average increase of 48% in odds of tutoring's frequency). As expected, the effect size decreases when adding more controls – that is, part of the effect is driven by self-selection of students to tutoring, based on observable characteristics. It is interesting to note that this reduction of effect size does not happen for the fifth model or controlling for enrollment in tutoring activities in the first semester. This latter result is expected since enrollment in tutoring during the first semester can be a predictor of enrollment in the second semester. The possible reason behind the non-effectiveness of the RtS nudging message is that weak students do not consider nor interpret their academic path as an investment for their future, or, at least, this does not happen at the end of their first semester of the first year, once they realized their difficulties in the academic adventure.

To explore the effectiveness of treatment, Table 2 shows the marginal effects (Average Marginal Effect, AME). Receiving the message leveraging on SC increases the probability of enrolling in tutoring activities, on average, by 2 percentage points (AME) respect to the control group. This result is statistically significant. On the contrary, RtS communication does not show any statistically significant impact on tutoring enrolment's decisions. AME allows to discuss the magnitude of the treatment effects, revealing that, despite its being significant in the case of SC, its impact is relatively low. However, as reported by Damgaard and Nielsen (2018), nudging is not claiming to obtain effects, that are substantial from a purely quantitative viewpoint since it is, by definition, a low-touch ('gentle') intervention. Also, these nudging interventions are also typically low-cost.

To deepen the potential mechanisms behind the intervention, treatment heterogeneity effects are explored. Table 3 presents the results from an exploration of heterogenous effects, showing the effect size of the interaction between treatments and pre-treatment covariates. Only covariates turning out with showing significant effects are shown, namely dropout probabilities and family income. Two interesting findings emerge from this analysis. First, the higher the dropout risk, the lower the probability of the student following the advice received with the nudging message – no matter the type. Students with a high associated dropout risk are less prone to consider advice finalized to continue education. Most likely, they are already pessimistic about the future of their academic success. Second, the social comparison leverage is more effective for students coming from low socio-economic backgrounds corroborating the idea that students' motivation is a driving force towards asking for additional support to improve their academic journey.

[Tables 2 and 3] around here

5. Managerial and policy implications

In this research, predicted dropout probabilities for student enrolled at PoliMi are used to organize and evaluate a differentiated nudging communication to convince them attending a tutoring service offered for free, in the spirit of developing an EWS with subsequent remedial intervention.

This paper aims at evaluating how different nudging communication may differently impact on at-risk students' behaviors, namely, on whether (or not) they enroll in tutoring activities. Interestingly, results show that the most effective nudging leverage to push at-risk students towards attending tutoring is the one adopting social comparison, i.e., suggesting students to benchmark their performance with that of "peers" who, in the past, benefited from the service.

By further exploiting the reasons behind the effectiveness of the nudging leverages, some potential mechanisms can be hypothesized. First, the perspective given by an alternative message based on returns to schooling is medium-term, forcing students to weight the potential benefits they could obtain after an educational investment (i.e., tutoring). For the population involved in this study this aspect could generate anxiety and discouragement, instead of optimism and engagement. Indeed, the target students are probably aware of the difficulties they are facing during their first semester and leveraging on their expected positive outcomes may lead them in realizing their (perceived) failure. Thus, those students are not expected to invest additional efforts and time in tutoring activities. On the other side, the perspective offered by the social comparison message leverages more on the "here and now". The perception of being part of a community, as introduced by Tinto (1998), associating their behavior to that of peers, is probably the key aspect of this message, stimulating a positive comparison with them. The analysis of heterogeneity highlights two mechanisms, i.e., the non-incremental effect of the nudging message on students based on dropout risk and the significant impact of the social comparison nudging message for students with lower socio-economic status. These aspects could be related to a lack (or, on contrary to a surplus) of motivation for pursuing the degree. Students with very high dropout risk (and probably aware of it) already feel out of university, while students asking for sacrifices are more motivated to stay on track and ask for academic support.

Our analysis shows promising results for future activities at Politecnico di Milano (PoliMi) and all the other universities that are defining methods for retaining their students at drop-out risk. The social comparison leverage should be kept for other communications, deepening the aspects that make it successful. In this case, the collaboration with researchers from different domains, such as behavioral one, is essential to capture all the possible communicative shades and evaluate the best option. The final goal of the policy maker is to find the optimal nudging intervention for different sub-samples of students. The potential of this approach is important, since the associated costs of this nudging are very low and the only constraint is time of its implementation: managers and analysts should wait to see (and measure) the effects of their intervention. However, the cost of tutoring is not considered in this computation, and therefore, future interventions should carefully evaluate the cost-benefit analysis of nudging interventions including all the costs for providing the tutoring services as a bundled part of this initiative.

For future research, experimental designers could also consider further innovations. First, predicted probabilities about students at risk could be obtained with different ML algorithms (such as neural networks). Second, the possibility to increase the intensity or varying the typology of the message may generate different effects, so additional formulation of alternative nudging messages should be further tested. Third, substituting emails with other forms of communication (like Whatsapp texts) may be another lever for improving effectiveness, especially given the higher level of engagement of students with different communication channels as for example social media like Instagram.

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Table 1 Descriptive statistics of student control variables - total and by treatment group

	Control (N=669)	*Social Comparison (N=687)*	*Returns to Schooling (N=644)*	*Total (N=2000)*	*p*-value
Dropout prob					0.546
- Mean (SD)	0.555 (0.193)	0.543 (0.192)	0.551 (0.193)	0.549 (0.193)	
- Range	0.241 - 0.899	0.241 - 0.899	0.241 - 0.899	0.241 - 0.899	
		Demographics			
Gender					0.678
- F	119 (17.8%)	135 (19.7%)	120 (18.6%)	374 (18.7%)	
- M	550 (82.2%)	552 (80.3%)	524 (81.4%)	1626 (81.3%)	
Origin					0.165
- Commuter (ref.)	424 (63.4%)	424 (61.7%)	408 (63.4%)	1256 (62.8%)	
- Foreigner	38 (5.7%)	62 (9.0%)	37 (5.7%)	137 (6.8%)	
- Milanese	171 (25.6%)	157 (22.9%)	161 (25.0%)	489 (24.4%)	
- Offsite	36 (5.4%)	44 (6.4%)	38 (5.9%)	118 (5.9%)	
Family income					0.652
- High bracket (ref.)	248 (37.1%)	276 (40.2%)	236 (36.6%)	760 (38.0%)	
- Low bracket	80 (12.0%)	73 (10.6%)	63 (9.8%)	216 (10.8%)	
- Medium bracket	121 (18.1%)	119 (17.3%)	126 (19.6%)	366 (18.3%)	
- Study grant	220 (32.9%)	219 (31.9%)	219 (34.0%)	658 (32.9%)	
		Previous studies			
Admission Test Score					0.83
- Mean (SD)	0.577 (0.145)	0.579 (0.136)	0.574 (0.129)	0.577 (0.137)	
- Range	0.076 - 1.000	0.080 - 1.000	0.102 - 1.000	0.076 - 1.000	
High school grade					0.168
- Mean (SD)	0.770 (0.196)	0.771 (0.192)	0.753 (0.193)	0.765 (0.194)	
- Range	0.213 - 1.000	0.000 - 1.000	0.344 - 1.000	0.000 - 1.000	
Previous Studies					0.551
- Scientifica (ref.)	434 (64.9%)	461 (67.1%)	448 (69.6%)	1343 (67.2%)	
- Classica	34 (5.1%)	40 (5.8%)	37 (5.7%)	111 (5.5%)	
- Others	54 (8.1%)	50 (7.3%)	43 (6.7%)	147 (7.3%)	
- Tecnica	147 (22.0%)	136 (19.8%)	116 (18.0%)	399 (19.9%)	
First semester tutoring enrolment					
Tutoring (1sem)					0.467
- 0 (no)	528 (78.9%)	541 (78.7%)	523 (81.2%)	1592 (79.6%)	
- 1 (yes)	141 (21.1%)	146 (21.3%)	121 (18.8%)	408 (20.4%)	

Note: The table provides descriptive statistics for first-year students predicted at risk of dropout and assesses the balance among groups. Summary statistics are reported in terms of absolute number and percentage for categorical variables, and mean, standard deviation, and range for the numerical ones. p–values in the last column refer to the Chisq-test of independence for categorical variables and to the t-test/Wilcoxon test of means comparison for numerical ones.

Table 2 Evaluation of differentiated nudging message for at-risk students

	Dependent variable: *Tutoring (2sem.) 2021/22*				
	Model 1	Model 2	Model 3	Model 4	Model 5
Nudging communication = SC	**0.415***	**0.406***	**0.385***	**0.383***	**0.390***
	(0.225)	*(0.225)*	*(0.226)*	*(0.228)*	*(0.230)*
Odds ratio	*1.5142*	*1.5012*	*1.4693*	*1.4662*	*1.4767*
Marginal effects	*0.0248*	*0.0242*	*0.0227*	*0.0223*	*0.0223*
Nudging communication = RtS	**−0.022**	**−0.025**	**−0.021**	**−0.004**	**−0.039**
	(0.249)	*(0.249)*	*(0.250)*	*(0.251)*	*(0.254)*
Odds ratio	*0.9783*	*0.9752*	*0.9795*	*0.9960*	*0.9621*
Marginal effects	*-0.0010*	*-0.0012*	*-0.0010*	*-0.0001*	*-0.0018*
Dropout prob. control:	no	yes	no	no	no
Demographic control:	no	no	yes	yes	yes
Previous studies control:	no	no	no	yes	yes
Tutoring 1st sem. control:	no	no	no	no	yes
Observations	2,000	2,000	2,000	2,000	2,000
Log Likelihood	−454.211	−452.768	−449.994	−441.550	−408.446
Akaike Inf. Crit.	914.423	913.535	919.987	913.100	848.892

Note: The Table shows the effect of the diversified nudging communication for at-risk students by sequentially adding more controls to the model. In bold highlighted, β_2 and β_3, while in parenthesis related standard deviations. Then, odds ratios and marginal effects are shown in italics to better interpret the magnitude of the effects. It is worth highlighting that the dropout probabilities are computed with predictive algorithms that use as inputs variables the rest of the covariates. For this reason, in Model 2 the only control is the predicted dropout probabilities. Significance legend: * p<0.1; **p<0.05; ***p<0.01.

Table 3 Heterogeneous effect of differentiated nudging message

	Dependent variable:	
	Tutoring (2 sem.) 2021/22	
	Model 1	Model 2
CommunicationType = Control:dropout prob	**-1.215**** ***(0.568)***	
CommunicationType = SC:dropout prob	-0.410 *(0.523)*	
CommunicationType = RtS :dropout prob	**-1.077*** ***(0.564)***	
CommunicationType = Control:family income=High		0.591 *(0.453)*
CommunicationType = SC:family income=High		0.441 *(0.457)*
CommunicationType =RtS:family income=High		0.606 *(0.452)*
CommunicationType = Control:family income=Low		0.037 *(0.699)*
CommunicationType = SC:family income=Low		**1.262**** ***(0.512)***
CommunicationType =RtS:family_income=Low		-0.994 *(1.079)*
CommunicationType = Control:family income=Medium		0.438 *(0.541)*
CommunicationType = SC:family income=Medium		0.702 *(0.509)*
CommunicationType =RtS:family income=Medium		0.657 *(0.522)*
CommunicationType = Control:family income=SG		0.165 *(0.503)*
CommunicationType = SC:family income=SG		**0.915**** ***(0.441)***
Controls	*no*	*yes*
Observations	2,000	2,000
Log Likelihood	-452.837	-403.500
Akaike Inf. Crit.	913.674	851.000

Note: The table reports the results of the heterogeneity analysis considering the interaction between covariates and treatment. In detail, it shows the β-coefficients of significant interactions with the treatments (i.e., predicted dropout probabilities and family income). Regression in Model 2 controls for all the pre-treatment covariates, except for *family income*.

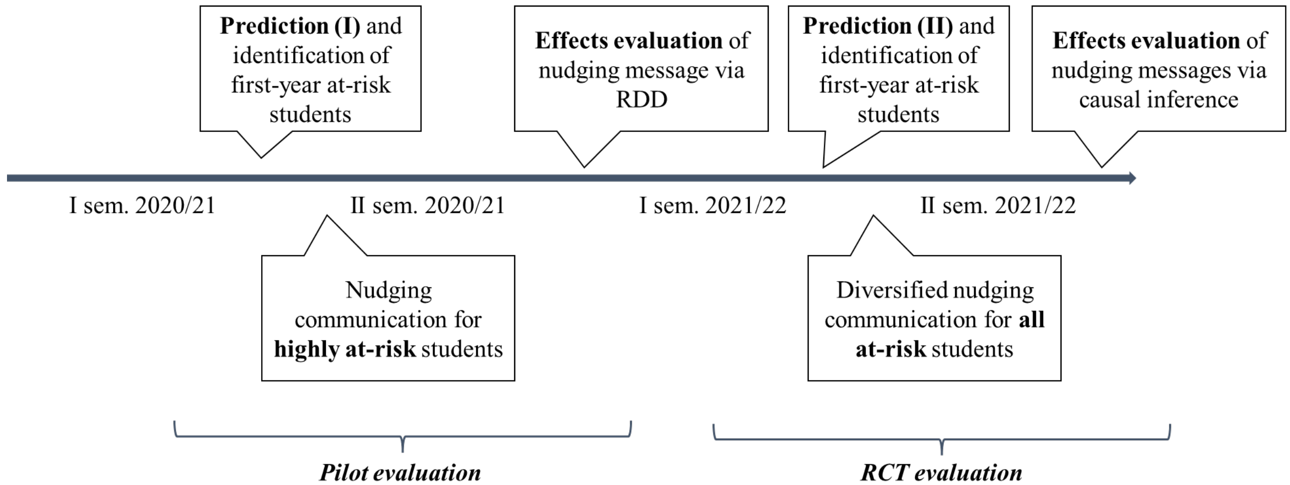
TECHNICAL ANNEX

Annex A; Table A1 Literature summary of relevant nudging evaluations in Education

Authors and publication year	Country and year of experiment	Population	Treatment	Goal	Results
Castleman and Page 2015	USA, 2012	College-intending students	Automated and personalized text messaging campaign	Increase college enrolment	Interventions substantially increased college enrolment
Castleman and Page, 2016	USA, 2012-2013	College freshmen (first-year students)	Personalized text messaging intervention	Maintain students' financial aid for the next academic year	Large and positive effects
Castleman and Meyer 2020	USA, 2013-2016	Students with low socio-economic status enrolling in college	Sent simplified information, encouragement, and access to one-on-one advising	Improving academic outcomes of students	No significant effects on freshman year credits.
Gurantz et al. 2020	USA, 2017	Students between high school and college	Virtual advising	Increase in post-secondary enrolment in selective colleges	No impact on overall college enrolment, but increased enrolment in high graduation rate colleges.
Bird et al. 2017	USA, 2015-2016	Students between high school and college	Scaling up the text messaging campaign	Remind students to enrol to college	No significant effects on college enrolments
Avery et al. 2021	USA, 2016	Students between high school and college	Two text messaging campaigns	Remind students about support with key steps in enrolling in college	Positive but minor effects in the national sample, while significant improvements in the context of Texas schools
Castleman and Page 2017	USA, 2014	High school students and their parents	Personalized outreach about tasks to complete to enrol in college	Improvement of college enrolment outcomes	Significant increase in college enrolment, but no effects' increase when involving parents
van Lent and Souverijn 2017	The Netherlands, 2014-2015	First-year students enrolled in undergraduate programs with academic mentors	Encouragement to set a course-specific grade goal	Improve academic outcomes	Greatest and significant benefits when goals are reachable

Note: The table summarizes the key characteristics (population, treatment, goal, and results of the studies) of the most recent and relevant evaluations about nudging in Higher Education Institutions. Most academic works are taken from the meta-analysis of Damgaard and Nielsen (2018).

Annex A, Figure A1 Experiment timeline from 2019 to 2021



Note: The figure shows the main steps of this research work. Research started with the first dropout prediction at the end of the first semester of A.A. 2020/2021, which allowed us to start the preliminary research work briefly described in Section 3.2 and detailed in Technical Annex B and C. Using the predicted dropout probabilities associated to first-year students, the 90% threshold was adopted to send a nudging communication to those above it, reminding them to enroll in tutoring. The evaluation of this first attempt (after the second semester of A.A. 2020/2021) provided non-significant results, setting the stage for the next experiment (object of this paper). Again, when the first semester of A.A. 2021/2022 came to an end, the second round of predictions were computed, the students at risk of dropout were randomly assigned to the different nudging communication treatments and their effect at the end of the second semester of A.A. 2021/2022 was evaluated (Section 3.3).

Annex A, Table A2 Student-level control variables

Variable name	Definition	Type
Stud_gender	Student's gender (M/F)	Categorical
Origins	Students' residency and domicile: - Commuter: the student lives out of the city - Foreigner: the student is not Italian - Milanese: the student lives in the city - Offside: the student moved to the city from outside	Categorical
Stud_admission_score	Student's admission test score	Numerical
Highschool_grade	Student's high school final grade	Numerical
PreviousStudies	Student's high school track: - Scientifica: general track on scientific studies - Classica: general track on classical studies - Technical: work-oriented studies - Other	
Family_income	Student's Uuniversity fee bracket: - High: highest fee bracket - Medium: medium fee bracket - Low: lowest fee bracket - SG: student with a study grant	Categorical

Note: The Table provides an overview of the control variables (pre-treatment) adopted in the subsequent evaluation, specifying their definition and type

Annex B. The effectiveness of attending tutoring services on academic performance

During the 2020/21 academic year, an analysis to test the tutoring effectiveness has been carried out at Politecnico di Milano (PoliMi). The aim was to test whether tutoring activities improve the academic careers of at-risk students. Propensity Score Matching (PSM) is adopted to compare students with a predicted dropout probability higher than 80%, who enroll (Treated) and do no enroll (Control) in tutoring services during their second semester. The bottom limit considered for this evaluation (80%) is chosen to select only those students with a high risk of dropout.

Once students with similar pre-treatment features (listed in Table A1) have been matched, they are paired according to their participation to tutoring services. PSM allows to compute the Average Treatment on the Treated (ATT) effect of attending tutoring. The final sample comprised 448 matched students: 224 belonging to treatment group and 224 to control.

Technical detail about PSM

The PSM allows to evaluate the treatment's effect in a quasi-experimental setting (i.e., not assuring randomized assignment between treatment and control groups). This approach provides researchers with analytic tools to mimic randomization, accounting for both observable and unobservable differences between treatment and control groups (in our case, the enrolment in tutoring activities) on the academic performance (Grade Point Average and credits obtained in the second semester of the first year).

Specifically, the propensity of observations (students) to be treated (going to tutoring), $p(x) = P(D = 1|x) = E(D|x)$, where D expresses the treatment assignment (1 for treatment, 0 for control), is estimated using logistic regression. The propensity score is the conditional (predicted) probability of receiving the treatment given pre-treatment characteristics x (student-level features) reported in Annex A.

Each student's predicted probability p(x), or propensity, to enroll in tutoring services forms the basis for matching tutoring participants with non-participants. Once students are matched according to mostly similar propensity scores (in this case, Neighbor matching), a final linear regression is computed to capture the effects of tutoring on the students' academic careers:

$$y_i = \alpha_{0i} + \boldsymbol{\alpha}_{1i} * \mathbf{x}_i + \epsilon_i \qquad (2)$$

where y_i represents the outcomes of the academic career (GPA and credits) at the end of the second semester for student *i* and $\mathbf{x}_i$ represents the student's level covariates. Table A2 shows the difference (in terms of variable balancing) before and after applying Propensity Score Matching.

Annex B, Table B1 Descriptive statistics by groups from Propensity Score Matching

	Control (N=224)	**Treatment** (N=224)	**Total** (N=448)	***p-value***
Access to study age				
Mean (SD) of matched sample	0.954 (0.073)	0.947 (0.082)	0.950 (0.078)	0.379
Mean (SD) of unmatched sample	0.929 (0.132)	0.947 (0.082)	0.935 (0.118)	0.057

	Control (N=224)	Treatment (N=224)	Total (N=448)	p-value
Gender				
Mean (SD) of matched sample	0.665 (0.473)	0.692 (0.463)	0.679 (0.468)	0.545
Mean (SD) of unmatched sample	0.789 (0.408)	0.692 (0.463)	0.755 (0.430)	0.006
Citizenship				
Mean (SD) of matched sample	0.951 (0.217)	0.902 (0.298)	0.926 (0.262)	0.047
Mean (SD) of unmatched sample	0.974 (0.160)	0.902 (0.298)	0.949 (0.220)	< 0.001
Admission score				
Mean (SD) of matched sample	0.515 (0.142)	0.513 (0.133)	0.514 (0.137)	0.925
Mean (SD) of unmatched sample	0.517 (0.132)	0.513 (0.133)	0.516 (0.132)	0.742
High school grade				
Mean (SD) of matched sample	0.614 (0.251)	0.585 (0.254)	0.599 (0.253)	0.236
Mean (SD) of unmatched sample	0.558 (0.249)	0.585 (0.254)	0.567 (0.251)	0.180
Previous Studies				
Mean (SD) of matched sample	0.612 (0.488)	0.621 (0.486)	0.616 (0.487)	0.846
Mean (SD) of unmatched sample	0.659 (0.475)	0.621 (0.486)	0.646 (0.479)	0.334
Family Income (matched sample)				0.164
High	95 (42.4%)	74 (33.0%)	169 (37.7%)	
Low	19 (8.5%)	27 (12.1%)	46 (10.3%)	
Medium	36 (16.1%)	45 (20.1%)	81 (18.1%)	
LS	74 (33.0%)	78 (34.8%)	152 (33.9%)	
Family Income (unmatched sample)				0.343
High	156 (37.0%)	74 (33.0%)	230 (35.6%)	
Low	65 (15.4%)	27 (12.1%)	92 (14.2%)	
Medium	74 (17.5%)	45 (20.1%)	119 (18.4%)	
LS	127 (30.1%)	78 (34.8%)	205 (31.7%)	
Student's origins (matched sample)				0.578
Commuter	162 (72.3%)	157 (70.1%)	319 (71.2%)	
Foreigner	7 (3.1%)	13 (5.8%)	20 (4.5%)	
Milanese	46 (20.5%)	44 (19.6%)	90 (20.1%)	
Off-site student	9 (4.0%)	10 (4.5%)	19 (4.2%)	
Student's origins (unmatched sample)				0.16
Commuter	286 (67.8%)	157 (70.1%)	443 (68.6%)	
Foreigner	12 (2.8%)	13 (5.8%)	25 (3.9%)	
Milanese	105 (24.9%)	44 (19.6%)	149 (23.1%)	
Off-site student	19 (4.5%)	10 (4.5%)	29 (4.5%)	

Note: The table presents the descriptive statistics of the control variables before and after matching. The p-values for comparison tests between treated and control groups confirm that the matching works, with more balanced characteristics afterwards. For the definition of variables, please refer to Table A1.

Results

The results showed in Table A3 consider the GPA and the credits obtained at the end of the second semester (of the first year) as outcome variables of interest. The first glaring result is the important contribution of the treatment: for at-risk students the enrolment in tutoring services is highly beneficial to improve their academic career in the short run. Indeed, at-risk students enrolled in tutoring services obtained positive and significant results, gaining 5.77 credits more than the control, and 2.63 points more on the GPA, on average. To summarize the main results obtained by the analysis, we can state that tutoring activities are on average effective in improving academic results of predicted at-risk students in the short run.

Annex B, table B2 Evaluation of the participation to tutoring activities on academic performance, Propensity Score Matching

Outcome	Mean in group 0	Mean in group 1	Difference	ATT
Credits	24.486	29.415	-2.744***	5.7781 ***
GPA	17.991	20.266	-3.133 ***	2.6306 ***

Note: Group 0 is the Control group while Group 1 is the Treated one

Annex C: The effectiveness of the nudging message: findings from the pilot study

Experimental Design

As described in Section 3.1, at the end of the first semester of the academic year 2020/2021, a dropout predicted probability is computed for each freshman. Students with a predicted high risk of dropout – the threshold was set at 90% - received a nudging communication via email from the university. The message, sent at the end of the first semester of the first year by the administrative offices, reminds students to enroll in tutoring activities to improve their academic career. The text of the email was the following: "*Dear student, Politecnico di Milano is strongly interested in ensuring that its students continue their training path with enthusiasm and passion within the university. We encourage you to consider tutoring courses, which can help improve your academic career with the help of other students like you. We are waiting for you!*". It should be noted that this communication was not personalized, nor it referred to the students' level of dropout risk. The main objective of the message was to reach out to students about taking into consideration the initiatives organized by the university to support students with difficulties in some subjects. Further, tutoring services are completely free-of-charge and participation is optional and flexible.

The methodological approach adopted to answer the research question is based on the Regression Discontinuity Design (RDD) to evaluate whether the nudging message can favor at-risk students' enrolment in tutoring activities. Sharp RD is used in this case, since the treatment status is a deterministic function of a covariate x_i (the running variable), i.e., the dropout probability. This variable has a known cutoff (x_0), which uniquely assigns each observation i to treatment or control, as follows:

$$D_i = \begin{cases} 1 \; if \; x_i > x_0 \\ 0 \; if \; x_i \leq x_0 \end{cases}$$

In our case, treatment D_i is defined based on the dropout predicted probability x_i and the cut-off $x_0 = 90\%$. The RDD regression can be formalized as follows (Angrist and Pischke, 2008):

$$y_i = \alpha + \beta x_i + \rho D_i + \epsilon_i \qquad (4)$$

where y_i is the outcome variable of interest, ρ is the causal effect of interest and x_i is the estimated dropout probability. The idea behind this formulation lays on the fact that the answer variable Y_i can be seen as:

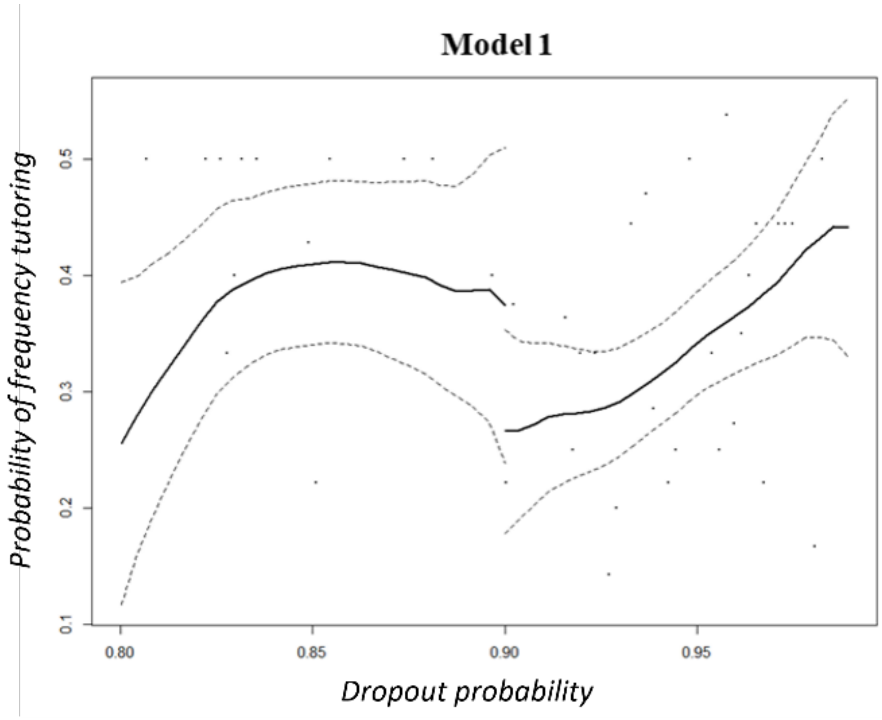
$$Y_i = \begin{cases} Y_{0i} \quad if \quad D_i = 0 \\ Y_{1i} \quad if \quad D_i = 1 \end{cases}$$

where Y_{0i}, that represents the potential outcome when there is no treatment, can be modeled as $E[\, Y_{0i} \mid x_i \,] = \alpha + \beta x_i$. Considering a potential effect of the treatment on the outcome, Y_{1i} can be defined as $Y_{1i} = Y_{0i} + \rho$. This leads to Eq. (4).

Main findings

The assessment of the effectiveness of the nudging communication for at-risk students is shown in Figure C1 and Table C1). Models show no statistical difference around the cutoff, showing a null impact of the nudging message. Moreover, Figure A1 shows a negative gap near the cutoff, but a slight increase in the probability of enrolling in tutoring activities is registered afterwards. Also, if the bandwidth considered is doubled comprising all the available observations, the significance of the negative effect of nudging message increases, as shown by *p-value* (0.056) and *F-statistics* (2.55) in Table A4. This first and unexpected result, object of a further discussion in Section 5, represents the main finding of this research. The main message (i.e., the absence of any statistical evidence of an effect of the nudging message) represents the baseline for future research in this field, which is mainly driven by a trial-and error approach.

Annex C, figure C1Assessing the effect of the nudging communication on tutoring enrollment through RDD



Note: The figure shows the sharp discontinuity near the 90% of dropout risk, considering as dependent variable Tutoring (2sem.) 2020/21

Annex C, table C1 Summary of RDD evaluation of nudging message for at-risk students

	Dependent variable: Tutoring (2 sem.) 2020/21					
	Bandwidth	*Observations*	*Estimate*	*Std. Error*	*Pr(>|z|)*	*F-statistics*
LATE	0.06495	483	-0.1082	0.10307	0.29374	1.9452
Half-BW	0.03247	226	-0.1138	0.13169	0.38743	0.8002
Double-BW	0.1299	646	-0.1595	0.08374	0.05688	2.5517

Note: The Table shows the width of the bandwidth, the number of observations within it, the values of the ρ coefficients and the associated statistics (standard error, p-value and F-statistics).

Pilot's limitations

The design of the evaluation relies on a small-scale study, adopting an institutional low-touch tone in the sent message (Bird et al., 2021; Castleman and Meyer, 2020). However, the absence of any statistical significant results from the intervention brings to wonder about the nudging strategy. Damgaard and Nielsen (2018) suggest different leverages that can be adopted to reach out to individuals in the educational domain. Further, the adoption of a too high threshold (probability of dropout higher than 90%) for sending the nudging message represents a possible source of limitation. Indeed, the targeted group of students has probably already dropped out or decided to drop out when the nudging message was sent out. However, the positive effects of tutoring activities suggest continuing with nudging interventions reaching out to students as much as possible about possible ways to improve (and save) their academic careers.

Annex D: Texts of nudging messages used in this study

Communication to control group

"Dear student,

Politecnico di Milano is strongly interested in ensuring that its students continue their training path with enthusiasm and passion within the university. For this reason, tutoring courses have been organized for all students who intend to recover or deepen the knowledge of one or more courses.

At the link https://www.ingindinf.polimi.it/it/studenti/servizi/tutorato you can find details on the tutoring program. We are waiting for you!"

Social Comparison communication

"Dear student,

Politecnico di Milano is strongly interested in ensuring that all its students continue their training path with enthusiasm, passion, and success. For this reason, tutoring courses have been organized for all students who intend to recover or deepen the knowledge of one or more courses. Studies conducted on previous years at the Politecnico have shown how useful these activities are in improving the academic career of students like you who have encountered difficulties in their first exams.

At the link https://www.ingindinf.polimi.it/it/studenti/servizi/tutorato you can find details on the tutoring program. We are waiting for you!"

Returns to schooling communication

"Dear student,

Politecnico di Milano is strongly interested in ensuring that all its students continue their training path with enthusiasm, passion, and success. For this reason, tutoring courses have been organized for all students who intend to recover or deepen the knowledge of one or more courses. These courses help to face the university path at the Polytechnic which can require important efforts and sacrifices. However, the professional satisfactions that follow the graduation are testified by the majority of former students.

At the link https://www.ingindinf.polimi.it/it/studenti/servizi/tutorato you can find details on the tutoring program. We are waiting for you!"

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