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The admission process to the minor is characterized by rationing, resolved by random assignment of available slots to applicants. Exploiting the resulting exogenous variation for identification, we find that the program substantially improves data literacy among participants with low pre-treatment levels of numeracy. Despite the additional effort required by the program, we find no evidence of a slowdown in students' progress in their major, as they pass at least as many exams as their peers in the control group.

We also find evidence of positive spillovers on the GPA of students with lower initial numeracy. Finally, using follow-up survey data collected approximately two years after, we show that participants with low pre-treatment numeracy are more likely to be in paid employment.

More is more: short and long term effects of promoting data literacy on graduate students outcomes *

Margherita Fort[†], Annalisa Loviglio[†], Susanna Tinti[‡]

April 14, 2026

Abstract

We study the impact of a program designed to enhance data literacy on graduate students' skills and academic outcomes at a large Italian university. The program (i.e. a *minor*) targets students who are expected to have weak quantitative competences and offers 120-hour training focused on improving their ability to interpret and process data, in addition to the regular courses of the master's program in which students are enrolled (i.e. their *major*). The admission process to the *minor* is characterized by rationing, resolved by random assignment of available slots to applicants. Exploiting the resulting exogenous variation for identification, we find that the program substantially improves data literacy among participants with low pre-treatment levels of numeracy. Despite the additional effort required by the program, we find no evidence of a slowdown in students' progress in their *major*, as they pass at least as many exams as their peers in the control group. We also find evidence of positive spillovers on the GPA of students with lower initial numeracy. Finally, using follow-up survey data collected approximately two years after, we show that participants with low pre-treatment numeracy are more likely to be in paid employment.

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1 Introduction

As the world has become more complex and data oriented (Carmi and Yates, 2020; Fontichiaro and Oehrli, 2016; Wolff et al., 2016), the need to make citizens able to understand, interpret and manage data has gained relevance among both policy makers and researchers. These competencies fall under the broad umbrella of *data literacy*. Data literacy can be defined as the ability to search for, read, understand, interpret and communicate data, extracting meaningful information to support decision-making in everyday life.[1] Understanding and managing data are fundamental for everyday tasks, while a lack of such skills expose individuals to various risks – personal, social, physical and financial – while also limiting their ability to be proactive citizens (Carmi and Yates, 2020). From interpreting news conveyed through graphs, info-graphics, and statistical summaries to performing basic financial tasks, data literacy plays a crucial role. It may be framed as a lever for social justice and equality (Elisa Raffaghelli, 2020), an increasingly essential requirement for the labor market (Chise et al., 2021; Fayer et al., 2017; Windisch, 2015), and a necessarily skill for navigating modern life – including, for instance, online banking, e-commerce and the management of bureaucratic processes (Hanushek et al., 2015).

Despite the widely acknowledge importance of data literacy, proficiency in this area remains notably low in Italy. While no standardized measures of data literacy currently exists, related skills, such as numeracy – as measured by the Programme for the International Assessment of Adult Competencies (PIAAC) – can serve as a useful proxy.[2] The PIAAC results indicate that Italy scores below the OECD average, emphasizing the urgent

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[1]A range of alternative albeit similar definitions of data literacy can be found in the literature. In 2017, the European Commission introduced its own definition – alongside the concept of information literacy – describing it as the ability to search, read, and interpret data across various daily and academic communication contexts. The OECD, building on the definition proposed by Carlson et al. (2011), defines data literacy as "the ability to derive meaningful information from data, the ability to read, work with, analyze and argue with data, and understand what data mean, including how to read charts appropriately, draw correct conclusions from data, and recognize when data are being used in misleading or inappropriate ways". Wolff et al. (2016) analyze different definitions of data literacy and propose to describe data literacy as the ability to ask and answer real-world questions from large and small data sets through an inquiry process that considers ethical data use. This includes skills such as selecting, cleaning, analyzing, visualizing, critiquing, and interpreting data, as well as communicating data-driven narratives and incorporating data into a design process.

[2]According to the OECD, numeracy is defined as the ability to access, use, interpret, and communicate mathematical information and concepts to solve and manage problems in various contexts. This closely aligns with the broader concept of data literacy (OECD, 2016).

need for improvement in this domain (OECD, 2021, 2024).

This study presents evidence on the effectiveness of an interdisciplinary course launched by a large Italian University to enhance data literacy skills among graduate students who may not otherwise receive such training within their standard curriculum. The program is offered at no cost to all master's students enrolled at the host University, and applications exceed available slots.

Participants have the opportunity to attend a *minor* consisting of four 30-hours courses focused on data collection, management, and interpretation. Since the program has no prerequisites, admission is determined by random assignment, which we exploit to identify its causal effects. Moreover, we leverage pre-treatment numeracy levels to study heterogeneous effects across the skill distribution. Our results suggest that most students may benefit from the program, with the largest improvements in data literacy competencies observed among those who began with lower numeracy skills. For instance, our estimates show that a participant with a numeracy level one standard deviation (s.d.) below the sample average achieves a data literacy score nearly 0.5 s.d. higher on an assessment administered 6 months after the end of classes, compared to an otherwise identical student not exposed to the program. Importantly, these gains do not come at the expense of the students' primary university career. In fact, the additional coursework does not slow down the completion of their *major* degree, as participants pass at least as many exams as their peers in the control group. Furthermore, results suggest an improvement in the GPA of students with lower pre-treatment numeracy.

As highlighted by PIAAC results, non-STEM graduates have lower numeracy than STEM graduates, and may be at a disadvantage in the labor market.[3] Our findings suggest that university students who do not choose STEM majors can benefit from minor programs targeting transversal skills, such as data literacy. This additional training may help them better align their competencies with the demands of a rapidly evolving labor market (Ghodoosi et al., 2024), ultimately improving their employment prospects. This is supported by evidence from a follow-up survey conducted approximately two years after the program. In particular, we find that participants with low pre-treatment numeracy—who benefit the most from the program in terms of data literacy—are more likely to be in paid employment.

Finally, our study contributes to the broader debate about majors and minors choices, as well as admission policies in tertiary education (e.g., Bordon and Fu, 2015). In Italy,

[3]According to Table A.2.6 (N) of the Annex available online at `https://stat.link/eb8dxq`, non-STEM graduates, on average, have numeracy levels nearly 19 points lower than STEM graduates (0.32 s.d.).

as in most European countries, students enroll in specialized programs, with relatively inflexible curricula. By contrast, in countries such as the U.S. and Canada, specialization is postponed and a greater flexibility in course selection is allowed. Our findings suggest that offering students the opportunity to complement their major with minor programs targeting diverse skill sets may be beneficial.

The paper is structured as follows: Section 2 describes the institutional setting and data, providing information about the program design and selection procedure, and it illustrates the data used in the paper. Section 3 explains the empirical strategy adopted and illustrates the main results. Section 4 concludes.

2 Institutional setting and data

During the 2021-2022 academic year, a large Italian University launched a series of educational programs targeting students enrolled in master's degrees. These programs offered blocks of four master's-level courses and allowed students to obtain formal qualifications in addition to their primary master's degree. In what follows, we refer to these programs as *minor*. The rational behind these programs is to introduce thematic courses to enrich students' primary university career (their *major*) with interdisciplinary competencies, which are valuable for both further studies and future employment. Designed to address relevant contemporary themes through an interdisciplinary approach, minor programs integrate conventional teaching with innovative methodologies, incorporating multimedia materials and group projects into lectures and seminars.

These programs were open to students already enrolled in a two-year master's degree at the host University and were offered free of charges.[4] All educational activities were conducted in person. In order to obtain the final certification, students were required to complete four courses and pass the corresponding exams.

Within this institutional framework, we focus on a specific *minor* titled *Learning from data* (LEDA), explicitly designed to promote *data literacy*. This program offers an interdisciplinary curriculum aimed at fostering a culture of knowledge centered on data comprehension and communication. The focal theme revolves around the concept of data literacy, emphasizing the importance of interpreting data, extracting meaningful information, and develop basic data management skills as a valuable addition to students' academic profiles.

[4]Students enrolled in three-year bachelor's degrees were not eligible and could not apply. The University also offers a small number of 5 or 6-year degrees (mainly in the medical field), whose students were eligible provided that they were in their fourth year or beyond.

The program combines 4 courses offered by different University Departments (Computer Science and Engineering, Statistical Sciences, Management, and Economics) over approximately 10 months. Two courses began in mid-February 2022, while the remaining two started in September 2022.[5] Each course offers a field-specific perspective within the common goal of introducing students to data literacy and enhancing their analytical skills, particularly for those whose academic backgrounds includes minimal exposure to quantitative subjects. In line with this objective, only students enrolled in master's degrees outside the four contributing departments were eligible for LEDA.

Application and Take-up Application opened in December 2021. All students interested in LEDA were required to complete the "Education & Skills Online Assessment" as part of the application process. This questionnaire is designed to provide individual-level results linked to the OECD's *Survey of Adult Skills (PIAAC)* measures of literacy and numeracy.[6] Aggregate statistics on performance in the assessment were shared with LEDA's governance and instructors to document the heterogeneous background of the class, while students did not receive any feedback.

The program received 150 applications, of which 109 were valid, for 50 available seats.[7] All applicants were informed that, due to limited capacity, admission would be determined by random assignment, stratified by five areas: humanities, social sciences, technology, science, and medicine. 51% of valid applications came from students in humanities programs and 30% were from students in social sciences (Law, Sociology or Political Sciences), suggesting a much higher interest in the program among students pursuing non-quantitative majors.

Applicants offered a seat had a few days to enroll. In the event of withdrawal, the slot was offered to the next candidate on the waiting list within the same academic area. Overall, 62 students were offered admission, and 48 choose to enroll, while 47 were not selected.[8] Unfortunately, the only available participation measure is exam completion: as of June 2023, 23 out of 48 students had passed at least one exam.[9]

[5]Specifically, the courses are: i) *Extracting, integrating and mining from complex sources* (Computer Science and engineering department); ii) *Describing phenomena and controlling uncertainty* (Statistical Sciences department); iii) *Managing data to support business activities* (Management Department); and iv) *Data to inform political and social choices* (Economics department).

[6]Further information is available at `https://www.oecd.org/en/about/programmes/piaac/education-and-skills-online-assessment.html`.

[7]Among the 150 applicants, 24 applicants were deemed ineligible for the program, while 17 failed to complete the entry test in due time and were thus excluded.

[8]Two seats remained vacant due to late withdrawals, which prevented further enrollment from the waiting list.

[9]By the end of the first exam session in June 2023, 16% of applicants assigned to the program completed

Endline Assessment Information on students' data literacy competencies was collected through an assessment specifically designed for the LEDA minor. The questionnaire was administered in June 2023, roughly 6 months after the courses ended, to capture long-lasting effects of the program rather than temporary improvements and to allow students to have at least one opportunity to take the exam at the end of each class. Students were invited to participate to the endline survey and were offered a flat incentive of 20 euros.[10] A total of 85 students completed the questionnaire, including 48 of those who were offered a slot in LEDA (77%) and 37 of those who did not have the chance to enroll (79%).

The assessment aimed to evaluate students' proficiency in applying logical-mathematical reasoning to real-world problems, as well as their ability to understand and interpret tables and graphs. It was based on GRE and GMAT validated tests and included 15 questions to be solved in approximately 40 minutes. Our main outcome of interest is the total number of correct answers.

Progression in the main career We complemented application and survey data with administrative data on students' performance in their major. Specifically, we retrieved from the host University archives the number of exams passed from the start of each student's master's program up to April 2023, along with the corresponding grades. This allows us to compute the number of exams passed before and after the start of the LEDA coursework in March 2022, as well as students' GPA. [11]

Follow-up survey To overcome the lack of access to administrative data on students' labor market outcomes, we conducted a follow-up survey designed to capture medium and long-term effects of the LEDA program. Data were collected in November 2025. The survey was administered online (CAWI) and could be completed in about five minutes.[12]

all four exams, 8% completed three exams, 6.5% completed 2 exams, 6.5% completed 1 exam. Although some students did not complete exams, they may have attended classes and benefit from the treatment nonetheless.

[10]The incentive scheme included a small penalty of 5 euros for students who took more than ten days to complete it since invitation, however only 3 students received the reduced amount of 15 euros. Out of the 109 students with valid application, 4 students did not give consent to be contacted at the end of the LEDA program and were thus not invited to complete the endline survey (two of them were offered a slot to participate to the program and two were not offered a slot).

[11]In Italy, exams are graded on a 30-point scale, with 18 as the minimum passing grade. The GPA is computed as a weighted average of passed exams, with weights proportional to university training credits (1 credit is considered equivalent to 25 hours of work; 60 credits correspond to one year of coursework). Only exams with grades are included. A small number of other activities assessed on a pass/fail basis (eg. apprenticeships, RAships, qualifying examinations, ...) are not included.

[12]A CATI (Computer Assisted Telephone Interviewing) protocol was implemented for individuals who did not respond to the initial invitation. The CATI protocol was used for 19 respondents.

All respondents received 10 euros upon completing the survey, provided they held PayPal credentials. Out of the 105 LEDA invited applicants, 93 (88.6%) completed the follow-up survey.[13] Respondents provided information on whether they had completed their master's degree at the time of the survey, their current labor market attachment, and their future prospects over a five-year horizon.

We construct several outcome variables from the follow-up survey.[14] First, we define a binary indicator for having completed the main master's degree at the time of the survey. Second, we measure labor market status through two indicators: a dummy equal to one if the respondent reports being in paid employment (including PhD candidates), and a dummy equal to one if the respondent reports being actively searching for a job. Third, we consider outcomes capturing individuals' perceptions about their future prospects, specifically career progression and earnings growth over the next five years.[15] Finally, we construct an index of the perceived importance of analytical skills for future careers, combining responses to questions on the importance of data literacy and analytical thinking.[16]

Descriptive statistics Table A.1 describes the sample of 109 applicants and one of the endline respondents used in the paper, grouped into Non-STEM (humanities and social sciences) vs STEM (technology, science, and medicine) disciplinary areas. We remind readers that, given eligibility criteria illustrate before, majors in Economics, Management, Statics and Computer Science and Engineering are excluded. The vast majority of applicants comes from Non-STEM fields and about 70% of applicants is female.[17] As expected, numeracy levels are lower for the Non-STEM group ($\approx$ 13 points, roughly 0.5 of a standard deviation of the corresponding score in this sample), while literacy levels are more similar ($\approx$ 6 points higher for Non-STEM fields applicants, roughly 0.15 of a

[13]We invited all applicants to LEDA who gave explicit consent to be contacted again when consent to participation and data processing was collected for the main outcomes in the earlier version of the manuscript.

[14]Appendix C reports the relevant questions asked in the survey.

[15]Respondents rate the extent to which they agree with the statements "In five years I will have good earning potential" and "In five years I will have good opportunities for professional growth". Responses range from 0 (do not agree at all) to 100 (fully agree), with 50 anchored as "neither agree nor disagree".

[16]Questions are measured on a 0 (not important) – 100 (of utmost importance) scale, with 50 anchored as "important". We construct the index by first standardizing each response using the mean and standard deviation of the non-assigned group participating in the follow-up assessment, and then standardizing their average using the same reference group, so that the final variable has mean 0 and standard deviation 1 in the control group. We also ask employed respondents to rate the importance of the same skills in their current occupation.

[17]There is some indication there female applicants are more likely to answer endline survey. However, there is no evidence of non random attrition along any observed covariate.

standard deviation of the corresponding score). STEM applicants are also more likely to hold an Academic High School degree, compared to Non-STEM fields applicants.

Approximately 50% of non-STEM applicants and 30% of STEM applicants are enrolled in the first year of their master's program. Non-STEM applicants passed an average of 5.9 exams in their main degree program, compared to 9.5 among STEM applicants. This difference is not surprising, given the higher proportion of STEM students who are at a more advanced stage in their studies. Pre-treatment grade point average (GPA) is similar across applicants from non-STEM and STEM fields.[18]

3 Empirical strategy and findings

We aim to assess the causal effect of the LEDA minor program on students' data literacy competencies. Additionally, we investigate potential spillover effects that attending extra courses may have on students' primary university careers. Specifically, we examine whether the additional workload has any negative impact on their performance in their major. We then use follow-up survey data to explore the long-term effects of the LEDA program training of the probability of graduating from their major and labor market condition and prospects.

We exploit the random variation introduced by the application process for identification: applicants were offered a slot to enroll in LEDA ("assigned") or not ("not assigned" or "controls") based on their position in a randomly sorted list. Panel a) of Table A.2 compares pre-treatment characteristics between these two groups, showing no significant differences. This confirms that the two groups are well balanced in terms of sex, year of enrollment in their major, and baseline literacy and numeracy, pre-treatment performance indicators in their major as well as secondary school type of education. Panel b) replicates the analysis for the subsample of students who completed the endline questionnaire, confirming that assigned and control students did not self-select differently when choosing to participate in the assessment.[19]

Specification choices We first estimate the *intention-to-treat* (ITT) effects, that is, the effect of being offered a slot to enroll in LEDA on digital literacy, academic performance in the primary career (short-term: extensive margin - number of exams; intensive margin-

[18]We replicate these descriptive statistics for the subsample of students who completed the follow-up survey and obtain consistent results. These additional tables are available upon request and are not reported here in the interest of space.

[19]Results are confirmed conditioning on the sample of applicants who also completed the follow-up survey.

endline GPA;long-term: probability of graduating from the major) and long-term labor market outcomes (probability to be in paid occupation or on the job search about two years after the end of the program and future prospects). Specifically, we estimate the following model:

$$Y_i = \alpha A_i + \gamma N_i + \mu_i + \epsilon_i \tag{1}$$

where Y_i represents the outcome of interest for student i, A_i equals 1 if the student was offered a slot, N_i denotes the pre-treatment level of numeracy, μ_i is the area fixed effect, and ϵ is an error term. Furthermore, in our preferred specification, we allow for heterogeneous effects based on pre-treatment numeracy levels by introducing an interaction term:

$$Y_i = \alpha' A_i + \beta' A_i \times N_i + \gamma' N_i + \nu_i + \varepsilon_i, \tag{2}$$

Next, we estimate the effect of LEDA using a parametric *instrumental variable* (IV) approach, where our baseline estimates consider a binary indicator for actual program enrollment.[20] The indicator is interacted with the pre-treatment level of numeracy in the specification allowing for heterogeneous effects by numeracy. Not surprisingly, given the high take-up rate, the instrument is not-weak, as confirmed in Table A.3.[21] Moreover, Table A.4 shows that sufficient independent sources of variation are detected for the model allowing for heterogeneous effects.

One might expect larger effects of the program would correspond to intense participation rather than mere enrollment. Appendix B explores an alternative take-up definition, based on actual participation. Since data on attendance are not available, we use the more restrictive binary indicator of having taken at least one of the four LEDA exams by the beginning of June 2023, before the endline assessment.

Effects of assignment and participation in LEDA on data literacy Figure 1 summarizes the main findings of our analysis on data literacy. It displays the marginal effects of the LEDA program according to the baseline specification (dashed red line) and to our preferred specification, which allows for heterogeneity by pre-treatment numeracy

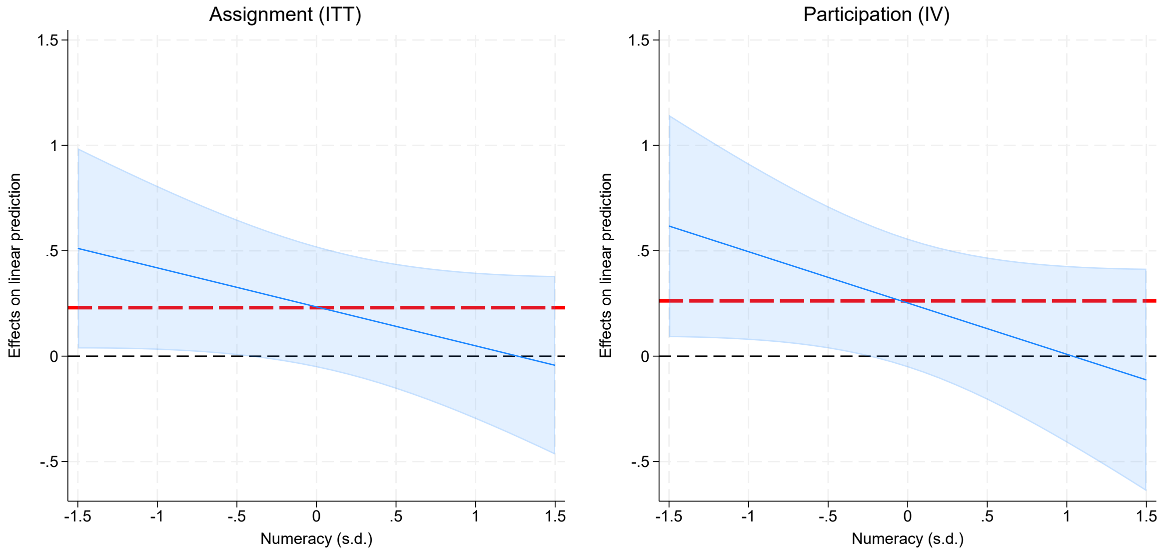
[20]We estimate the following model, using two-stage least squares:

$$Y_i = aT_i + cN_i + m_i + e_i \tag{3}$$
$$T_i = pA_i + qN_i + r_i + u_i, \tag{4}$$

where T_i equals 1 if the student enrolled in LEDA. The interaction term $A_i \times N_i$ is included as second instrument in the specification that accounts for heterogeneous effects by numeracy.

[21]The first-stage estimate of the probability of enrollment is 87.7%. The estimate is not sensitive to the omission of the control for pre-treatment levels of numeracy (see Table A.3 in the Appendix).

Figure 1: Effect of the LEDA program on data literacy



Note: The figure displays estimates of the marginal effects of being assigned to LEDA (left panel) or enrolling in LEDA (right panel), based on the ITT (left panel) or IV (right panel) estimates or the model that allows for heterogeneity by pre-treatment levels of numeracy reported in the last two columns of Table A.5 in the Appendix. Each estimate is complemented with a 90% confidence interval based on the asymptotic distribution of corresponding estimators and estimates of parameters and standard errors from the same table. The horizontal red dashed lines reports the marginal effects estimated through the models that do not allow for heterogeneity (first columns of Table A.5).

levels (solid blue line). The left panel presents results for the ITT specifications, while the right panel shows results for the IV ones. Corresponding estimates can be found in Table A.5 in the Appendix.

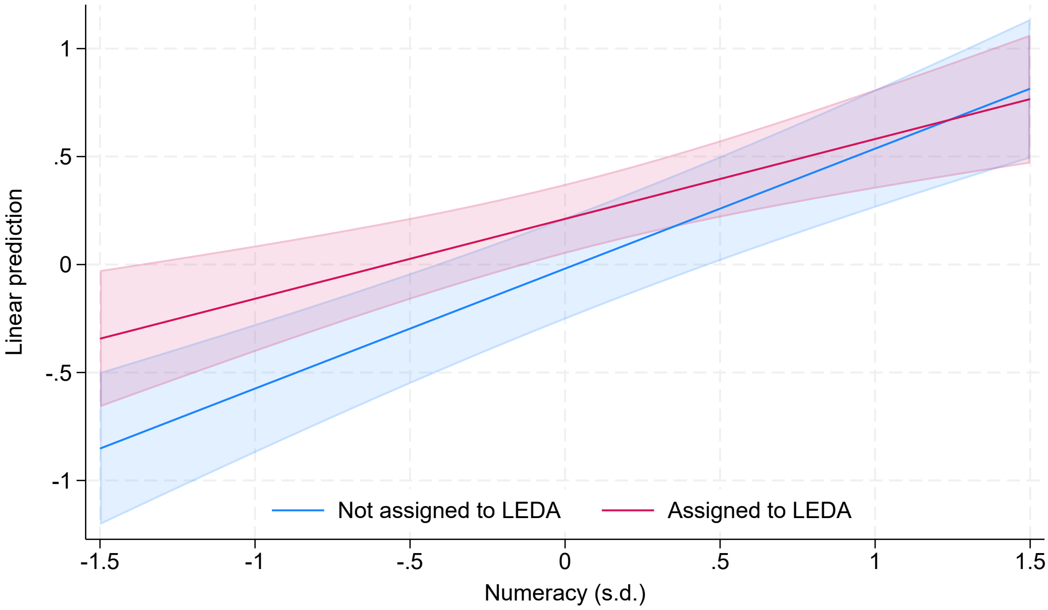
Results suggest an average increase of data literacy by more than 0.2 standard deviations (0.23 s.d. in the ITT specification and 0.26 in the IV specification), though these estimates are not statistically significant.[22] However, there is evidence of heterogeneity along pre-treatment numeracy levels, with students with lower numeracy benefiting the most from the program. We detect statistically significant and large effects for individuals with below average numeracy: for instance, the ITT marginal effect of LEDA for students with numeracy 1 s.d. below average is 0.42.[23] Conversely, we find small and non-statistically significant effect for individuals with above average numeracy.

We find reassuring that the program benefited students with low pre-treatment levels

[22]P-values are 0.19 for the ITT specification and 0.17 for the IV specification.

[23]The one-sided p-value for H_1 : marginal effect for individuals with pre-treatment levels of numeracy 1 s.d. below average > 0 is 0.037.

Figure 2: Predicted level of data literacy by baseline numeracy



Note: The figure shows predictions of expected values of data literacy based on the ITT parameter estimates of the model that allows for heterogeneity by pre-treatment levels of numeracy reported in Table A.5 in the Appendix. Each estimate is complemented with a 90% confidence interval based on the asymptotic distribution of corresponding estimators and estimates of parameters and standard errors from the same table.

of numeracy and, at the very least, did not harm those with high pre-treatment numeracy.

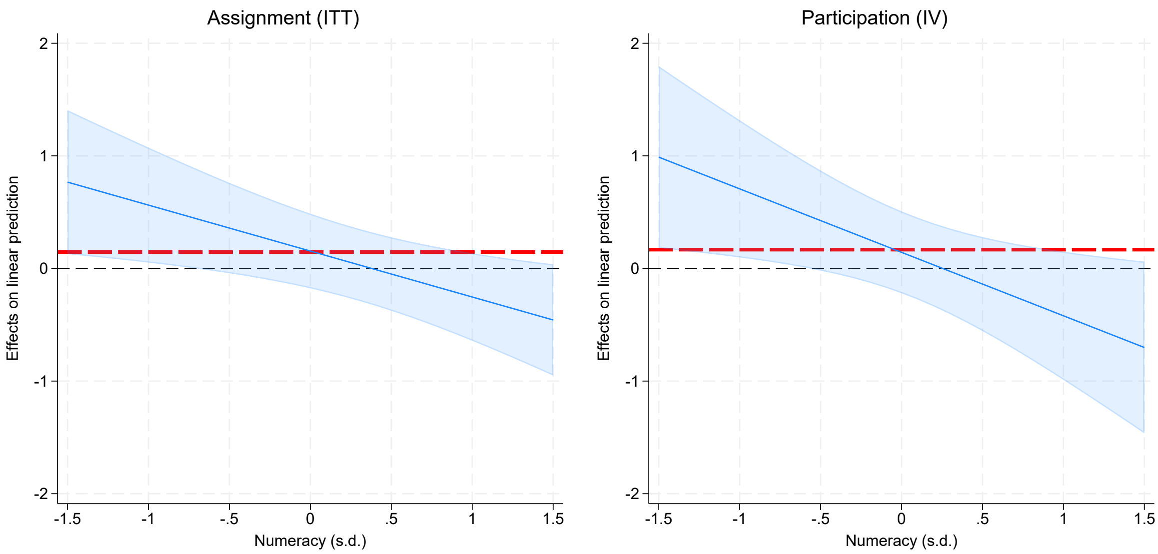
IV estimates further confirm positive and sizable effects on data literacy for individuals who start with lower numeracy levels (0.50 s.d. for those with numeracy 1 s.d. below the mean) and negligible effects for those with above average levels of numeracy.

Figure 2 highlights a positive correlation between data literacy and pre-treatment numeracy among both controls students and those assigned to LEDA. However, this correlation is weaker for the latter, indicating that the program may help individuals compensate for initially low numeracy levels.

Overall, our results suggest that LEDA has a positive or null effects for applicants, and show a large gain for those with lower initial numeracy. We interpret these findings as evidence that the program acts as an equalizer, reducing gaps between individuals who are better equipped in terms of quantitative skills and those with weaker initial endowments.

Effects of assignment and participation in LEDA on primary career While positively impacting data literacy, the program could also generate negative spillover effects on students' progress in their primary degree by slowing down their academic advancement.

Figure 3: Effect of the LEDA program on GPA at LEDA program endline from major degree by baseline numeracy



Note: The figure displays estimates of the marginal effects of being assigned to LEDA (left panel) or enrolling in LEDA (right panel), based on the ITT (left panel) or IV (right panel) estimates or the model that allows for heterogeneity by pre-treatment levels of numeracy reported in the last two columns of Table A.5 in the Appendix. Each estimate is complemented with a 90% confidence interval based on the asymptotic distribution of corresponding estimators and estimates of parameters and standard errors from the same table. The horizontal red dashed lines reports the marginal effects estimated through the models that do not allow for heterogeneity (first columns of Table A.5).

To assess this possibility, we examine the effect of LEDA on both the number of exams passed (the "extensive margin") and GPA (the "intensive margin") after the start of the program in winter 2022.

As reported in Table A.6 in the Appendix, we do not detect any statistically significant effect on the extensive margin. If anything, LEDA appears to have a small positive average effect on the number of exams passed, with larger – though still statistically insignificant – gains for those with low pre-treatment numeracy.[24]

Furthermore, LEDA has positive but insignificant average effects on the intensive margin and sizable and significant effects for students with low pre-treatment numeracy. As shown in Figure 3, for students with numeracy 1 s.d. below the mean, the estimated effects correspond to increases of 0.55 grade points (ITT) and 0.69 grade points (IV), that

[24]On average control students passed 3.6 exams, with a standard deviation of 2.9. Thus, the estimated effects in Table A.6 for students with 1 s.d. below-average numeracy correspond to improvements of 0.11 s.d. (ITT) and 0.13 s.d. (IV).

is, approximately 0.6 s.d. (ITT) and 0.7 s.d. (IV).[25]

Overall, the results are reassuring in that the program did not generate negative effects on students' primary degree's progress, and suggest positive spillovers for participants with lower pre-treatment numeracy.

Effects of assignment and participation in LEDA on long-term outcomes Figure 4 summarizes the main findings of our analysis on long-term outcomes, measured approximately two years after the end of the LEDA program. It displays the marginal effects of the LEDA program according to the baseline specification (dashed red line) and to our preferred specification, which allows for heterogeneity by pre-treatment numeracy levels (solid blue line). The left panel reports ITT results, while the right panel shows IV results. Corresponding estimates can be found in Tables A.8 and A.9 in the Appendix.

We first examine whether participation in LEDA affects the probability of graduating from the main master's program. Consistent with results on exams passed, we do not find evidence of an impact. Estimated average effects are close to zero, with positive but statistically insignificant effects for students with low pre-treatment numeracy.

We then turn to labor market outcomes and investigate whether LEDA affects the probability of being in paid employment. The average effect is positive but not statistically significant. However, positive and statistically significant effects emerge for individuals with low pre-treatment numeracy, who experience a substantial increase in their probability of being in paid employment. As shown in Table A.10 in the Appendix, nearly symmetric results are obtained when considering the probability of being on the job search as the outcome. The average effect is negative but not statistically significant, while we detect a large and significant reduction in the probability of job search among individuals with initially low numeracy levels. These findings mirror the short-term effects of the program on data literacy and suggest that the training generates persistent benefits in the labor market, particularly for initially weaker individuals.

As summarized in Table A.11 and Table A.12 in the Appendix, despite the positive effects on employment, we do not detect significant differences between the treatment and control groups in terms of expectations about future career outcomes, specifically career progression and earnings growth over the next five years.

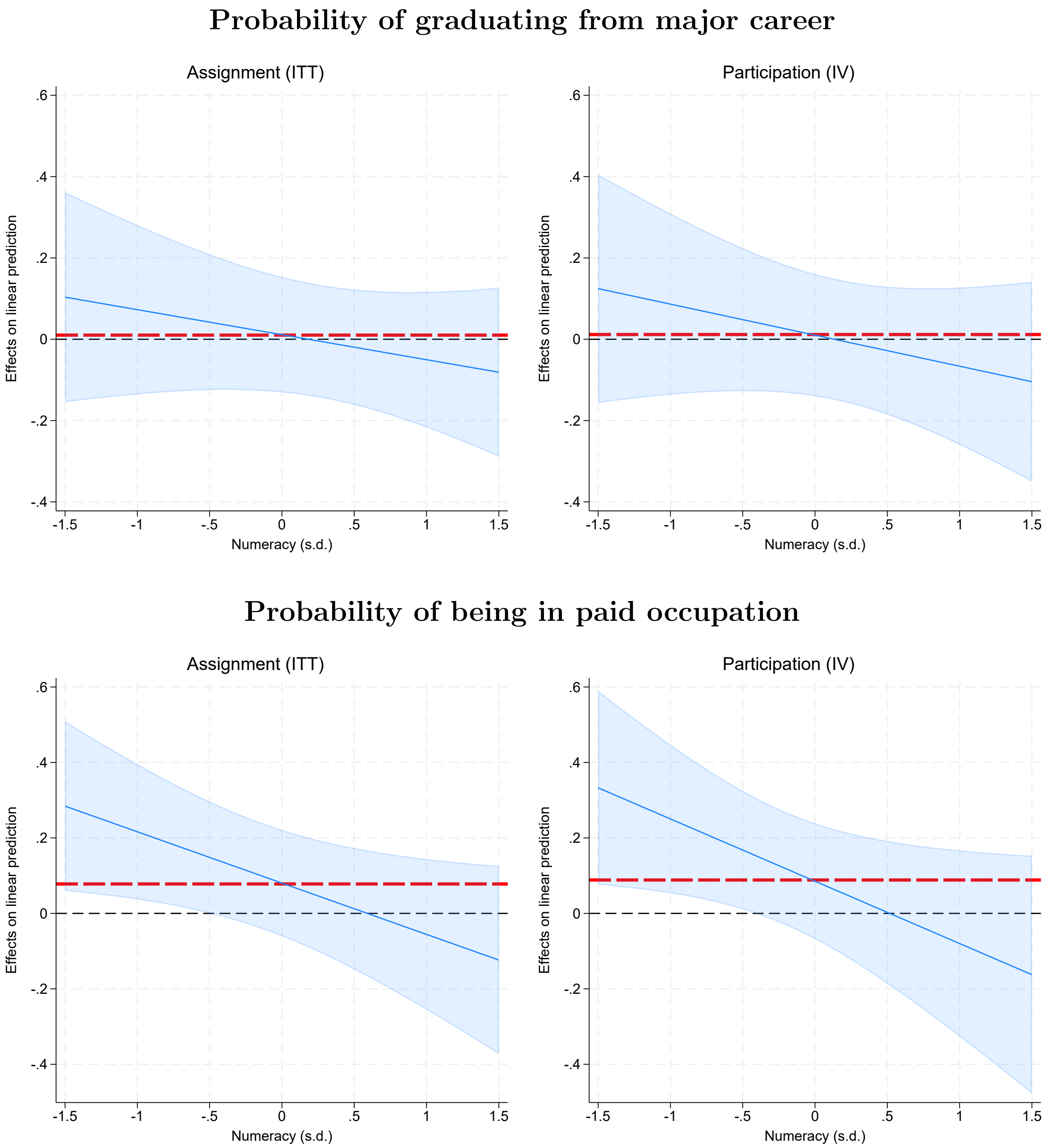
We also consider as an outcome the perceived importance of analytical skills for future careers, measured as an index combining two questions on the importance of data literacy and analytical thinking (as explained in Section 2). Interestingly, individuals in both the treatment and control groups assign a high importance to these skills (average ratings of

[25]Corresponding estimates can be found in Table A.7 in the Appendix.

77 for data literacy and 90 for analytical thinking on a 0–100 scale, where 50 corresponds to "important"), suggesting that recent graduates are well aware of the relevance of these competencies in the labor market. We then test whether LEDA affects this perceived importance (see Table A.13 in the Appendix). While participants tend to report slightly higher values of the index, the differences are not statistically significant.[26]

[26]We also do not detect significant differences in the self-reported use of analytical skills in the current occupation. However, these results should be interpreted with caution, as this outcome is only observed for employed individuals, and LEDA itself affects labor market participation.

Figure 4: Effect of the LEDA program on long-run outcomes two years after the end of the program by baseline numeracy



Note: The figure displays estimates of the marginal effects of being assigned to LEDA (left panel) or enrolling in LEDA (right panel), based on the ITT (left panel) or IV (right panel) estimates or the model that allows for heterogeneity by pre-treatment levels of numeracy reported in the last two columns of Tables A.8and A.9. Each estimate is complemented with a 90% confidence interval based on the asymptotic distribution of corresponding estimators and estimates of parameters and standard errors from the same table. The horizontal red dashed lines reports the marginal effects estimated through the models that do not allow for heterogeneity (first columns of Tables A.8 and A.9.).

4 Concluding Remarks

We study the causal effects of the LEDA data literacy program, offered as a complement to students' primary degree programs at a large Italian University. Rationing of available slots is resolved through random assignment of applicants to the program, allowing us to exploit a clean identification strategy to assess causal effects. Notably, given this design, the exogenous source of variation is independent from students' pre-treatment numeracy levels, which were measured using a standardized OECD assessment at baseline. Thus, we explore the heterogeneity in the program's effects based on students' initial competencies.

We find that students with lower baseline numeracy skills benefit significantly from the program, experiencing substantial improvements in data literacy as measured by an assessment administered six months after course completion. In contrast, we detect small or negligible effects for students with above-average numeracy skills. Importantly, LEDA does not slow down students' progresses in their primary career. We find no evidence of negative effects on the number of exams passed and, if anything, students with lower numeracy slightly increase the number of exams taken, although the effect is not statistically significant. At the same time, we find evidence of positive spillovers on academic performance, as students with lower pre-treatment numeracy experience improvements in their GPA.

Given the limited precision of our estimates, these results should be interpreted with some caution. Nonetheless they suggest that offering training on data literacy to adults - such as master's students at university - can yield substantial benefits and has the potential to reduce inequalities in data literacy. Consistently, our findings indicate that interventions targeting individuals with expected low levels of data literacy may be effective in improving these essential transferable skills.[27]

Importantly, a follow-up survey conducted approximately two years later suggests that these improvements in skills also translate into labor market outcomes. In particular, we find that participants with lower pre-treatment numeracy—who benefit the most in terms of data literacy—are more likely to be in paid employment. This result suggests that training in data literacy may improve early labor market outcomes for individuals with weaker quantitative backgrounds.

[27]This paper uses data collected up to June 2023. While we initially planned to extend the analysis with additional waves of data collection, institutional constraints prevented this. First, the LEDA program was temporarily discontinued for one year. Second, when it was recently re-instated, the selection process changed, and rationing was no longer resolved through randomization. As a consequence, the new edition of the program does not allow us to implement the same identification approach to increase statistical power.

Beyond the many non-economic reasons to invest in the skills of both youth and adults – including the view that a minimum level of literacy and numeracy is a civil right and a prerequisite for full participation in a modern democracy (Vignoles, 2016), the literature has documented a strong association between numeracy skills and labor market outcomes. For instance, Hanushek et al. (2015) report that in Italy a one-standard-deviation increase in numeracy is associated with a 13.2% increase in hourly wages among prime-age workers. Under the strong assumption that gains in data literacy translate into labor market returns similar to those of numeracy, back-of-the-envelope calculations suggest that a training program targeting data literacy could lead to a 6.5% wage increase for individuals starting with low quantitative skills.[28] This estimate should be interpreted with caution, as returns to quantitative skills are likely to vary across occupations, and individuals from different fields of study may sort into jobs with different skill requirements. However, it provides a useful benchmark to highlight that the economic impact of improving data literacy is likely to be meaningful. Furthermore, while larger-scale studies would be necessary to confirm and extend our evidence, our results on early employment outcomes for individuals with weaker quantitative backgrounds are encouraging and point to the potential for data literacy training to generate economically meaningful returns.

Such returns could be particularly relevant for graduates from non-STEM fields, who typically have lower quantitative skills, potentially contributing to narrow the wage gap between STEM and non-STEM graduates. According to the main survey of Italian graduates, five years after graduation the wage gap between Humanities and STEM graduates exceeds 22%.[29] Under the assumptions discussed above, our back-of-the-envelope calculations suggest that data literacy training for Humanities graduates could reduce this gap by up to 5 percentage points, closing almost one fourth of it. While differences in occupational choices across fields may limit the extent to which such gains materialize, our follow-up survey shows that individuals from non-STEM programs also assign high importance to data literacy for their future careers, suggesting that these skills are relevant across a wide range of occupations.[30]

Overall, the evidence presented in this paper may encourage further investment in data literacy training, as well as additional research aimed at better understanding the labor

[28] This back-of-the-envelope calculation multiplies 13.2% by 0.49, the IV estimate for students with pre-treatment numeracy 1 s.d. below average (from Table A.5).

[29] Authors' computation using AlmaLaurea national averages. Data available at `www.almalaurea.it/i-dati/le-nostre-indagini/condizione-occupazionale-laureati`

[30] 85% of respondents from non-STEM programs (84% among Humanities) and 90% of respondents from a STEM program report that data literacy will be an important competence for their career over the next five years. Consistently, among employed respondents, a substantial share of non-STEM graduates also report that data literacy is relevant for their current occupation.

market impact of programs that develop transversal skills such as data literacy.

Declaration of generative AI and AI-assisted technologies in the writing process During the preparation of this work A. Loviglio used Chatgpt in order to improve readability of selected paragraphs. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

References

Bordon, P., Fu, C., 2015. College-major choice to college-then-major choice. The Review of Economic Studies 82, 1247–1288.

Carlson, J., Fosmire, M., Miller, C., Nelson, M.S., 2011. Determining data information literacy needs: A study of students and research faculty. Libraries and the Academy 11, 629–657.

Carmi, E., Yates, S.J., 2020. What do digital inclusion and data literacy mean today? Internet Policy Review 9.

Chise, D., Fort, M., Monfardini, C., 2021. On the intergenerational transmission of stem education among graduate students. The BE Journal of Economic Analysis & Policy 21, 115–145.

Elisa Raffaghelli, J., 2020. Is data literacy a catalyst of social justice? A response from nine data literacy initiatives in higher education. Education Sciences 10, 233.

Fayer, S., Lacey, A., Watson, A., 2017. Stem occupations: Past, present, and future. Spotlight on Statistics 1, 1–35.

Fontichiaro, K., Oehrli, J.A., 2016. Why data literacy matters. Knowledge quest 44, 21–27.

Ghodoosi, B., Torrisi-Steele, G., West, T., Heidari, M., 2024. Perceptions of data literacy and data literacy education. Journal of Librarianship and Information Science .

Hanushek, E.A., Schwerdt, G., Wiederhold, S., Woessmann, L., 2015. Returns to skills around the world: Evidence from PIAAC. European Economic Review 73, 103–130.

OECD, 2016. Skills matter: Further results from the survey of adult skills. oecd skills studies. OECD Publishing .

OECD, 2021. The assessment frameworks for cycle 2 of the programme for the international assessment of adult competencies, OECD skills studies, OECD publishing, paris.

OECD, 2024. Do adults have the skills they need to thrive in a changing world?: Survey of adult skills 2023, OECD skills studies, OECD publishing, paris.

Vignoles, A., 2016. What is the economic value of literacy and numeracy? IZA World of Labor .

Windisch, H.C., 2015. Adults with low literacy and numeracy skills: A literature review on policy intervention .

Wolff, A., Gooch, D., Montaner, J.J.C., Rashid, U., Kortuem, G., 2016. Creating an understanding of data literacy for a data-driven society. The Journal of Community Informatics 12.

Appendix for the paper

The consequences of promoting data literacy amon graduate students by

Margherita Fort[1]; Annalisa Loviglio[2]; Susanna Tinti[3]

Appendix

Table of Contents

A Tables - baseline definition of the treatment

This section reports additional tables relevant to the paper.

Table A.1 describes the sample of 109 applicants and one of the endline respondents used in the paper, grouped into Non-STEM (humanities and social sciences) vs STEM (technology, science, and medicine) disciplinary areas. We stress that because of the eligibility criteria for the LEDA program, the STEM applicants do not include students enrolled in degrees in Computer Science and Engineering and the Non-STEM applicants do not include students enrolled in degrees in Economics, Management and Statistics.

Table A.2 compares the pre-treatment characteristics of students assigned to LEDA and those not assigned, on the sample of applicants and on the sub-sample of applicants who completed the endline survey.

Tables A.3 and A.4 report the first-stage estimates for specification without or with heterogeneous effects by numeracy, respectively. There is no indication of weak instruments issues, and sufficient independent sources of variation are detected for the models allowing for heterogeneous effects.

Tables A.5 show the ITT and IV estimates of participating in LEDA on data literacy using enrollment as proxy for participation.

Table A.6 report the effect on students' primary university career.

Tables A.13 and A.11 and A.12 report estimates of the effects on self-reported perceived importance of analytical skills and future labour market prospects (earnings and professional growth in 5 years). Each of the outcomes is standardized with respect to the sample of applicants not assigned to LEDA who completed the follow-up survey, consistently with the standardization approach used for the data literacy measure.

All tables include a baseline specification and a specification were we allow for heterogeneous effects based on pre-treatment numeracy levels.

Tables with corresponding first-stage, ITT and IV estimates using an alternative proxy for LEDA participation (i.e. exam taking behavior) are presented in Section B.

Table A.1: Descriptive Statistics

	LEDA Applicants		Endline respondents	
	Non-STEM fields	STEM fields	Non-STEM fields	STEM fields
Female	0.682	0.667	0.721	0.706
	(0.468)	(0.483)	(0.452)	(0.470)
Academic	0.580	0.762	0.544	0.882
High School	(0.496)	(0.436)	(0.502)	(0.332)
Literacy	332.727	329.048	333.971	328.235
	(38.139)	(37.935)	(39.517)	(40.502)
Numeracy	312.273	325.500	312.500	325.882
	(25.085)	(23.278)	(25.060)	(24.253)
	Main university career before LEDA (before March 2022)			
1° year Master	0.477	0.333	0.485	0.294
	(0.502)	(0.483)	(0.503)	(0.470)
N. exams^{+}	5.864	9.524	5.588	10.412
	(4.944)	(8.687)	(4.426)	(9.321)
GPA^{++}	28.669	28.623	28.686	28.695
	(1.368)	(1.100)	(1.284)	(1.215)
No exams^{+++}	0.080	0.048	0.103	0.059
	(0.272)	(0.218)	(0.306)	(0.243)
Observations	88	21	68	17

Note: The table reports descriptive statistics on pre-treatment characteristics of eligible students for the sample that includes all LEDA applicants who completed the follow-up survey (left panel) and the sub-sample who also completed the endline survey (right panel), by field of study. We stress that because of the eligibility criteria for the LEDA program, the STEM applicants do not include students enrolled in degrees in Computer Science and Engineering and the Non-STEM applicants do not include students enrolled in degrees in Economics, Management and Statistics. *Literacy* and *Numeracy* represent the PIAAC literacy and numeracy scores, in levels.$^{+}$ Number of graded exams taken before March 2022 by each students. $^{++}$ GPA is available only for students who took at least one graded exam before March 2022 and missing for students who did not take any graded exam before March 2022. Raw data record information on the weighted grade point average for each applicants, with weights proportional to university training credits (1 credit is considered equivalent to 25 hours of work; 60 credits correspond to one year of activity at University). $^{+++}$ The tables reports the average of a dummy variable taking the value 1 if the student took no graded exams before March 2022 and 0 otherwise. Figures in the table represent the share of students with no graded exams taken.

Table A.2: Balance of pre-treatment characteristics by assignment status

	Panel (a) LEDA Applicants			Panel (b) Endline respondents		
	Not-ass.	Assigned	Diff.	Not-ass.	Assigned	Diff.
Female	0.681	0.677	-0.021	0.703	0.729	0.006
	(0.471)	(0.471)	(0.097)	(0.463)	(0.449)	(0.104)
Academic	0.617	0.613	-0.021	0.568	0.646	0.029
High School	(0.491)	(0.491)	(0.099)	(0.502)	(0.483)	(0.112)
Literacy	330.213	333.387	3.564	332.162	333.333	1.357
	(38.813)	(37.545)	(7.883)	(40.766)	(38.994)	(9.145)
Numeracy	312.766	316.452	2.142	315.135	315.208	-1.952
	(27.560)	(23.195)	(4.940)	(28.735)	(22.690)	(5.591)
	Main university career before LEDA (before March 2022)					
1° year Master	0.404	0.484	0.082	0.378	0.500	0.139
	(0.496)	(0.504)	(0.098)	(0.492)	(0.505)	(0.112)
N. exams^{+}	7.085	6.177	-0.452	7.459	5.854	-1.195
	(6.975)	(5.126)	(1.008)	(7.486)	(4.491)	(1.051)
GPA^{++}	28.693	28.635	-0.122	28.691	28.699	-0.078
	(1.307)	(1.330)	(0.249)	(1.197)	(1.242)	(0.275)
No exams^{+++}	0.085	0.065	-0.019	0.108	0.083	-0.024
	(0.282)	(0.248)	(0.054)	(0.315)	(0.279)	(0.069)
Observations	47	62	109	37	48	85

Note: The table reports average characteristics of eligible students (mean and standard deviations) by assignment status and tests whether differences are statistically significant running independent OLS regressions, with robust standard errors. Consistently with the randomization design, all regressions include area fixed effects. The estimated difference and the corresponding standard error are reported in the Table. *Literacy* and *Numeracy* represent the PIAAC literacy and numeracy scores, in levels. $^{+}$ Number of graded exams taken before March 2022 by each students. $^{++}$GPA is available only for students who took at least one graded exam before March 2022 and missing for students who did not take any graded exam before March 2022. Raw data record information on the weighted grade point average for each applicants, with weights proportional to university training credits (1 credit is considered equivalent to 25 hours of work; 60 credits correspond to one year of activity at University). $^{+++}$ The tables reports the average of a dummy variable taking the value 1 if the student took no graded exams before March 2022 and 0 otherwise. Figures in the table represent the share of students with no graded exams taken. Legend:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. No significant differences detected.

Table A.3: Effect of being offered a slot for the LEDA program on participation (First Stage)

	No controls	Pre-treatment controls
	(1)	(2)
Assigned to LEDA	0.878^{***}	0.877^{***}
	(0.051)	(0.052)
Numeracy		-0.007
		(0.036)
Area fe	Yes	Yes
F-test	297.205	287.164
Adj. R-Square	0.699	0.696
Observations	85	85

Note: The table reports estimate of first stage parameters assessing the causal effect of being offered a slot for LEDA on participation to the program using linear probability model and OLS estimator for alternative specifications that differ for the control variables included on the sample of applicants who completed the endline survey. Our preferred specification is the one presented in column (2). IV estimates corresponding to specification in column (2) are presented in Table A.5 (data literacy) and Table A.6 and A.7 (students' main careers). Binary indicator for participation into LEDA is enrollment in the program (vs not enrollment). Consistently with the randomization design, all regression include area fixed effects. *Numeracy* is the standardized numeracy score based on PIAAC test. The indicator is standardized with respect to the 105 applicants to LEDA. Robust standard errors in parentheses. Legend:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Effect of being offered a slot for the LEDA program on participation (First Stage) - Models allowing for heterogenous effects by pre-treatment numeracy levels

	Enrollment (P)	
	P	P · Numeracy
Assigned LEDA	0.878***	-0.051
	(0.051)	(0.055)
Assigned LEDA · Numeracy	-0.046	0.712***
	(0.074)	(0.116)
Numeracy	0.014	-0.001
	(0.019)	(0.013)
Area fe	Yes	Yes
F-test	164.533	27.469
SW F-test	323.632	44.911
Observations	85	85

Note: The table reports estimate of first stage parameters assessing the causal effect of being offered a slot for LEDA on participation to the program using linear probability model and OLS estimator in a model were heterogeneous effects are allowed (see Tables A.5 for corresponding IV estimates on data literacy and Table A.6 for students' careers). The sample for the analysis includes applicants who completed the endline survey. Binary indicator for participation into LEDA is enrollment in the program (vs not enrollment) and it is denoted with P. Consistently with the randomization design, all regression include area fixed effects. *Numeracy* is the standardized numeracy score based on PIAAC test. The indicator is standardized with respect to the 105 applicants to LEDA. P is the participation indicator, either based on enrollment or on exams. Legend: SW for Sanderson-Windmeijer multivariate F test of excluded instruments. The SW complement the F-test on joint significance of the instrument as they are tests for under-identification and weak identification of individual endogenous regressors in models with multiple endogenous regressors and instruments. They check for "sufficient" independent source of variation, *partialling-out* linear projections of the remaining endogenous regressors. Robust standard errors in parentheses. Legend: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Effect of the assignment and of participation to the LEDA program on data literacy- ITT and IV results. Measure of participation based on: enrollment

	Model parameters' estimates			
	Baseline specification		Preferred specification	
	ITT	IV	ITT	IV
Assigned to LEDA	0.230		0.234	
	(0.173)		(0.172)	
Assigned to LEDA · Numeracy			-0.185	
			(0.139)	
LEDA Participant		0.262		0.252
		(0.190)		(0.186)
LEDA Participant · Numeracy				-0.243
				(0.174)
Numeracy	0.468***	0.470***	0.553***	0.549***
	(0.071)	(0.068)	(0.097)	(0.092)
Area fe	Yes	Yes	Yes	Yes
Observations	85	85	85	85
Assigned to LEDA (ITT)				
@**Low Numeracy** (-1sd) [m.e.]			**0.419***	
2-sided p-value (H_1 : m.effect $\neq 0$)			0.077	
@**High Numeracy** (+1sd) [m.e.]			**0.049**	
2-sided p-value (H_1 : m.effect $\neq 0$)			0.815	
LEDA **Participant** (IV)				
@**Low Numeracy** (-1sd) [m.e.]				**0.496***
2-sided p-value (H_1 : m.effect $\neq 0$)				0.052
@**High Numeracy** (+1sd) [m.e.]				**0.009**
2-sided p-value (H_1 : m.effect $\neq 0$)				0.972

Note: The table reports results on independent regression assessing: i) the causal effect of being offered a slot for LEDA on data literacy (ITT); i) the causal effect of participation to LEDA on data literacy (IV). See Table A.3 and Table A.4 for corresponding first stage estimates. The sample for the analysis includes applicants who completed the endline survey. Binary indicator for participation into LEDA is enrollment in the program (vs not enrollment). The Table reports estimates from two different model specifications (baseline and preferred), that differ as the preferred specification allows for heterogeneous effects based on pre-treatment numeracy Consistently with the randomization design, all regression include area fixed effects. *Numeracy* is the standardized numeracy score based on PIAAC test. The indicator is standardized with respect to the 105 applicants to LEDA. Robust standard errors in parentheses. Legend: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Effect of the assignment and of participation to the LEDA program on primary University career (number of exams) - ITT and IV results. Measure of participation based on: enrollment

	Model parameters' estimates			
	Baseline specification		Preferred specification	
	ITT	IV	ITT	IV
Assigned to LEDA	0.165		0.169	
	(0.646)		(0.649)	
Assigned to LEDA · Numeracy			-0.166	
			(0.634)	
LEDA Participant		0.188		0.179
		(0.707)		(0.716)
LEDA Participant · Numeracy				-0.221
				(0.860)
Numeracy	0.396	0.397	0.472	0.470
	(0.326)	(0.313)	(0.425)	(0.407)
Area fe	Yes	Yes	Yes	Yes
Observations	85	85	85	85
Assigned to LEDA (ITT)				
@**Low Numeracy** (-1sd) [m.e.]			**0.334**	
2-sided p-value (H_1 : m.effect $\neq 0$)			0.690	
@**High Numeracy** (+1sd) [m.e.]			**0.063**	
2-sided p-value (H_1 : m.effect $\neq 0$)			0.998	
LEDA **Participant** (IV)				
@**Low Numeracy** (-1sd) [m.e.]				**0.400**
2-sided p-value (H_1 : m.effect $\neq 0$)				0.677
@**High Numeracy** (+1sd) [m.e.]				**-0.042**
2-sided p-value (H_1 : m.effect $\neq 0$)				0.974

Note: The table reports results on independent regression assessing: i) the causal effect of being offered a slot for LEDA on main University career (number of exam passed after LEDA program activities start) (ITT); i) the causal effect of participation to LEDA on main University career (number of graded exam passed after LEDA program activities start) (see Table A.3 and Table A.4 for corresponding first stage estimates). The sample for the analysis includes applicants who completed the endline survey. The binary indicator for participation into LEDA is enrollment in the program (vs not enrollment). The Table reports estimates from two different model specifications (baseline and preferred), that differ as the preferred specification allows for heterogeneous effects based on pre-treatment numeracy Consistently with the randomization design, all regression include area fixed effects. *Numeracy* is the standardized numeracy score based on PIAAC test. The indicator is standardized with respect to the 105 applicants to LEDA. Robust standard errors in parentheses. Legend: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Effect of the assignment and of participation to the LEDA program on primary University career (GPA)- ITT and IV results. Measure of participation based on: enrollment

	Model parameters' estimates			
	Baseline specification		Preferred specification	
	ITT	IV	ITT	IV
Assigned to LEDA	0.127		0.136	
	(0.207)		(0.205)	
Assigned to LEDA · Numeracy			-0.410**	
			(0.186)	
LEDA Participant	0.145		0.144	
	(0.226)		(0.221)	
LEDA Participant · Numeracy			-0.567**	
				(0.287)
Numeracy	0.116	0.117	0.305**	0.302**
	(0.085)	(0.082)	(0.131)	(0.124)
Area fe	Yes	Yes	Yes	Yes
Observations	85	85	85	85
Assigned to LEDA (ITT)				
@**Low Numeracy** (-1sd) [m.e.]			**0.545***	
2-sided p-value (H_1 : m.effect $\neq 0$)			0.075	
@**High Numeracy** (+1sd) [m.e.]			**-0.274**	
2-sided p-value (H_1 : m.effect $\neq 0$)			0.275	
LEDA **Participant** (IV)				
@**Low Numeracy** (-1sd) [m.e.]				**0.689***
2-sided p-value (H_1 : m.effect $\neq 0$)				0.059
@**High Numeracy** (+1sd) [m.e.]				**-0.446**
2-sided p-value (H_1 : m.effect $\neq 0$)				0.227

Note: The table reports results on independent regression assessing: i) the causal effect of being offered a slot for LEDA on GPA in the main University career (ITT); i) the causal effect of participation to LEDA on GPA in the main University career (see Table A.3 and Table A.4 for corresponding first stage estimates). The sample for the analysis includes applicants who completed the endline survey. The binary indicator for participation into LEDA is enrollment in the program (vs not enrollment). The Table reports estimates from two different model specifications (baseline and preferred), that differ as the preferred specification allows for heterogeneous effects based on pre-treatment numeracy. Consistently with the randomization design, all regression include area fixed effects. *Numeracy* is the standardized numeracy score based on PIAAC test. The indicator is standardized with respect to the 105 applicants to LEDA. Robust standard errors in parentheses. Legend: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Effect of the assignment and of participation to the LEDA program on the probability of graduating from main University career - ITT and IV results. Measure of participation based on: enrollment. Sample: all follow-up respondents

	Model parameters' estimates			
	Baseline specification		Preferred specification	
	ITT	IV	ITT	IV
Assigned to LEDA	0.010		0.011	
	(0.085)		(0.085)	
Assigned to LEDA · Numeracy			-0.062	
			(0.075)	
LEDA Participant		0.012		0.012
		(0.093)		(0.138)
LEDA Participant · Numeracy				-0.076
				(0.088)
Numeracy	-0.011	0.011	0.018	0.018
	(0.038)	(0.037)	(0.050)	(0.052)
Area fe	Yes	Yes	Yes	Yes
N	93	93	93	93
	Hypothesis testing (p-values)			
Assigned to LEDA (ITT)				
@**Low Numeracy** (-1sd) [m.e.]			**0.073**	
2-sided p-value (H_1: m.effect $\neq 0$)			0.563	
@**High Numeracy** (+1sd) [m.e.]			**-0.050**	
2-sided p-value (H_1: m.effect $\neq 0$)			0.617	
LEDA **Participant** (IV)				
@**Low Numeracy** (-1sd) [m.e.]				**0.086**
2-sided p-value (H_1: m.effect $\neq 0$)				0.524
@**High Numeracy** (+1sd) [m.e.]				**-0.066**
2-sided p-value (H_1: m.effect $\neq 0$)				0.573

Note: The table reports results on independent regression assessing: i) the causal effect of being offered a slot for LEDA on regular University career (ITT); i) the causal effect of participation to LEDA on regular University career measured as the probability of graduating within about two years since the end of the LEDA program (self-reported) (see Table ?? and Table ?? for corresponding first stage estimates). The sample for the analysis includes applicants who the follow-up survey regardless whether they also completed the endline survey. Binary indicator for participation into LEDA is enrollment in the program (vs not enrollment). The Table reports estimates from two different model specifications (baseline and preferred), that differ as the preferred specification allows for heterogeneous effects based on pre-treatment numeracy Consistently with the randomization design, all regression include area fixed effects. *Numeracy* is the standardized numeracy score based on PIAAC test. The indicator is standardized with respect to the 105 applicants to LEDA. Robust standard errors in parentheses. Legend: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: Effect of the assignment and of participation to the LEDA program on primary university career, outcome: being in paid occupation, self-reported in November 2025. ITT and IV results. Measure of participation based on: enrollment. Sample: all follow-up respondents

	Model parameters' estimates			
	Baseline specification		Preferred specification	
	ITT	IV	ITT	IV
Assigned to LEDA	0.078		0.080	
	(0.086)		(0.085)	
Assigned to LEDA · Numeracy			-0.136*	
			(0.077)	
LEDA Participant		0.088		0.085
		(0.094)		(0.093)
LEDA Participant · Numeracy				-0.165*
				(0.099)
Numeracy	-0.037	-0.036	0.028	0.026
	(0.039)	(0.038)	(0.052)	(0.050)
Area fe	Yes	Yes	Yes	Yes
N	93	93	93	93
	Hypothesis testing (p-values)			
Assigned to LEDA (ITT)				
@**Low Numeracy** (-1sd) [m.e.]			**0.216****	
2-sided p-value (H_1: m.effect $\neq 0$)			0.048	
@**High Numeracy** (+1sd) [m.e.]			**-0.056**	
2-sided p-value (H_1: m.effect $\neq 0$)			0.645	
LEDA **Participant** (IV)				
@**Low Numeracy** (-1sd) [m.e.]				**0.250****
2-sided p-value (H_1: m.effect $\neq 0$)				0.036
@**High Numeracy** (+1sd) [m.e.]				**-0.080**
2-sided p-value (H_1: m.effect $\neq 0$)				0.595

Note: The table reports results on independent regression assessing: i) the causal effect of being offered a slot for LEDA on the probability of being in paid work within about two years since the end of the LEDA program (self-reported) (ITT); ii) the causal effect of participation to LEDA on the probability of being in paid work within about two years since the end of the LEDA program (self-reported) (IV). See Table**??** and Table **??** for corresponding first stage estimates. The sample for the analysis includes applicants who the follow-up survey regardless whether they also completed the endline survey. Binary indicator for participation into LEDA is enrollment in the program (vs not enrollment). The Table reports estimates from two different model specifications (baseline and preferred), that differ as the preferred specification allows for heterogeneous effects based on pre-treatment numeracy. Consistently with the randomization design, all regression include area fixed effects. *Numeracy* is the standardized numeracy score based on PIAAC test. The indicator is standardized with respect to the sample of applicants not assigned to LEDA. The indicator is standardized with respect to the 105 applicants to LEDA. Robust standard errors in parentheses. Legend: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: Effect of the assignment and of participation to the LEDA program on primary university career, outcome: looking for a job, self-reported in November 2025. ITT and IV results. Measure of participation based on: enrollment. Sample: all follow-up respondents

	Model parameters' estimates			
	Baseline specification		Preferred specification	
	ITT	IV	ITT	IV
Assigned to LEDA	-0.093		-0.094	
	(0.073)		(0.073)	
Assigned to LEDA · Numeracy			0.094	
			(0.070)	
LEDA Participant		-0.105		-0.103
		(0.079)		(0.080)
LEDA Participant · Numeracy				0.112
				(0.087)
Numeracy	0.030	0.029	-0.015	-0.013
	(0.033)	(0.031)	(0.048)	(0.045)
Area fe	Yes	Yes	Yes	Yes
N	93	93	93	93
	Hypothesis testing (p-values)			
Assigned to LEDA (ITT)				
@**Low Numeracy** (-1sd) [m.e.]			**-0.188***	
2-sided p-value (H_1: m.effect $\neq 0$)			0.055	
@**High Numeracy** (+1sd) [m.e.]			**-0.000**	
2-sided p-value (H_1: m.effect $\neq 0$)			0.997	
LEDA **Participant** (IV)				
@**Low Numeracy** (-1sd) [m.e.]				**-0.214****
2-sided p-value (H_1: m.effect $\neq 0$)				0.045
@**High Numeracy** (+1sd) [m.e.]				**0.009**
2-sided p-value (H_1: m.effect $\neq 0$)				0.947

Note: The table reports results on independent regression assessing: i) the causal effect of being offered a slot for LEDA on the probability of being on the hob search within about two years since the end of the LEDA program (self-reported) (ITT); ii) the causal effect of participation to LEDA on the probability of being on the hob search within about two years since the end of the LEDA program (self-reported) (IV). See Table ?? and Table ?? for corresponding first stage estimates. The sample for the analysis includes applicants who the follow-up survey regardless whether they also completed the endline survey. Binary indicator for participation into LEDA is enrollment in the program (vs not enrollment). The Table reports estimates from two different model specifications (baseline and preferred), that differ as the preferred specification allows for heterogeneous effects based on pre-treatment numeracy. Consistently with the randomization design, all regression include area fixed effects. *Numeracy* is the standardized numeracy score based on PIAAC test. The indicator is standardized with respect to the 105 applicants to LEDA. Robust standard errors in parentheses. Legend: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11: Effect of the assignment and of participation to the LEDA program on labor market expectations; outcome: earnings possibilities in 5 years, self-reported in November 2025. ITT and IV results. Measure of participation based on: enrollment. Sample: all follow-up respondents

	Model parameters' estimates			
	Baseline specification		Preferred specification	
	ITT	IV	ITT	IV
Assigned to LEDA	0.052		0.050	
	(0.226)		(0.229)	
Assigned to LEDA · Numeracy			0.152	
			(0.253)	
LEDA Participant		0.059		0.063
		(0.247)		(0.248)
LEDA Participant · Numeracy				0.194
				(0.302)
Numeracy	0.046	0.049	-0.026	-0.027
	(0.139)	(0.136)	(0.172)	(0.163)
Area fe	Yes	Yes	Yes	Yes
N	93	93	93	93
	Hypothesis testing (p-values)			
Assigned to LEDA (ITT)				
@**Low Numeracy** (-1sd) [m.e.]			**-0.103**	
2-sided p-value (H_1: m.effect $\neq 0$)			0.787	
@**High Numeracy** (+1sd) [m.e.]			**0.202**	
2-sided p-value (H_1: m.effect $\neq 0$)			0.502	
LEDA **Participant** (IV)				
@**Low Numeracy** (-1sd) [m.e.]				**-0.131**
2-sided p-value (H_1: m.effect $\neq 0$)				0.753
@**High Numeracy** (+1sd) [m.e.]				**0.363**
2-sided p-value (H_1: m.effect $\neq 0$)				0.480

Note: The table reports results on independent regression assessing: i) the causal effect of being offered a slot for LEDA on the self-reported earnings possibilities in 5 years (ITT); ii) the causal effect of participation to LEDA on the self-reported earnings possibilities in 5 years (IV). See Table ?? and Table ?? for corresponding first stage estimates. The sample for the analysis includes applicants who the follow-up survey regardless whether they also completed the endline survey. Binary indicator for participation into LEDA is enrollment in the program (vs not enrollment). The outcome in each equation is standardized with respect to the sample of applicants not assigned to LEDA who completed the follow-up survey. The Table reports estimates from two different model specifications (baseline and preferred), that differ as the preferred specification allows for heterogeneous effects based on pre-treatment numeracy. Consistently with the randomization design, all regression include area fixed effects. *Numeracy* is the standardized numeracy score based on PIAAC test. The indicator is standardized with respect to the 105 applicants to LEDA. Robust standard errors in parentheses. Legend: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: Effect of the assignment and of participation to the LEDA program on labor market expectations; outcome: professional growth possibilities in 5 years, self-reported in November 2025. ITT and IV results. Measure of participation based on: enrollment. Sample: all follow-up respondents

	Model parameters' estimates			
	Baseline specification		Preferred specification	
	ITT	IV	ITT	IV
Assigned to LEDA	0.064		0.063	
	(0.210)		(0.212)	
Assigned to LEDA · Numeracy			0.056	
			(0.217)	
LEDA Participant		0.073		0.074
		(0.229)		(0.230)
LEDA Participant · Numeracy				0.074
				(0.260)
Numeracy	0.040	0.041	0.014	0.013
	(0.130)	(0.126)	(0.161)	(0.153)
Area fe	Yes	Yes	Yes	Yes
N	93	93	93	93
	Hypothesis testing (p-values)			
Assigned to LEDA (ITT)				
@**Low Numeracy** (-1sd) [m.e.]			**0.008**	
2-sided p-value (H_1: m.effect $\neq 0$)			0.982	
@**High Numeracy** (+1sd) [m.e.]			**0.119**	
2-sided p-value (H_1: m.effect $\neq 0$)			0.668	
LEDA **Participant** (IV)				
@**Low Numeracy** (-1sd) [m.e.]				**0.001**
2-sided p-value (H_1: m.effect $\neq 0$)				0.999
@**High Numeracy** (+1sd) [m.e.]				**0.334**
2-sided p-value (H_1: m.effect $\neq 0$)				0.658

Note: The table reports results on independent regression assessing: i) the causal effect of being offered a slot for LEDA on self-reported professional growth possibilities in 5 years (ITT); ii) the causal effect of participation to LEDA on self-reported professional growth possibilities in 5 years (IV). See Table **??** and Table **??** for corresponding first stage estimates. The sample for the analysis includes applicants who the follow-up survey regardless whether they also completed the endline survey. Binary indicator for participation into LEDA is enrollment in the program (vs not enrollment). The outcome in each equation is standardized with respect to the sample of applicants not assigned to LEDA who completed the follow-up survey. The Table reports estimates from two different model specifications (baseline and preferred), that differ as the preferred specification allows for heterogeneous effects based on pre-treatment numeracy. Consistently with the randomization design, all regression include area fixed effects. *Numeracy* is the standardized numeracy score based on PIAAC test. The indicator is standardized with respect to the 105 applicants to LEDA. Robust standard errors in parentheses. Legend: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.13: Effect of the assignment and of participation to the LEDA program on primary university career, outcome: perceived importance of data literacy and analytical skills for future work opportunities over a 5-years horizon, self-reported in November 2025. ITT and IV results. Measure of participation based on: enrollment. Sample: all follow-up respondents

	Model parameters' estimates			
	Baseline specification		Preferred specification	
	ITT	IV	ITT	IV
Assigned to LEDA	0.069		0.069	
	(0.218)		(0.220)	
Assigned to LEDA · Numeracy			-0.030	
			(0.215)	
LEDA Participant		0.078		0.077
		(0.234)		(0.238)
LEDA Participant · Numeracy				-0.033
				(0.256)
Numeracy	0.063	0.064	0.077	0.076
	(0.111)	(0.107)	(0.135)	(0.129)
Area fe	Yes	Yes	Yes	Yes
N	93	93	93	93
	Hypothesis testing (p-values)			
Assigned to LEDA (ITT)				
@**Low Numeracy** (-1sd) [m.e.]			**0.099**	
2-sided p-value (H_1: m.effect $\neq 0$)			0.762	
@**High Numeracy** (+1sd) [m.e.]			**0.040**	
2-sided p-value (H_1: m.effect $\neq 0$)			0.890	
LEDA **Participant** (IV)				
@**Low Numeracy** (-1sd) [m.e.]				**0.110**
2-sided p-value (H_1: m.effect $\neq 0$)				0.757
@**High Numeracy** (+1sd) [m.e.]				**0.045**
2-sided p-value (H_1: m.effect $\neq 0$)				0.896

Note: The table reports results on independent regression assessing: i) the causal effect of being offered a slot for LEDA on the perceived importance of data literacy and analytical skills for future work opportunities over a 5-years horizon (ITT); ii) the causal effect of participation to LEDA on the perceived importance of data literacy and analytical skills for future work opportunities over a 5-years horizon (IV). See Table **??** and Table **??** for corresponding first stage estimates. The sample for the analysis includes applicants who the follow-up survey regardless whether they also completed the endline survey. Binary indicator for participation into LEDA is enrollment in the program (vs not enrollment). The outcome in each equation is standardized with respect to the sample of applicants not assigned to LEDA who completed the follow-up survey. The Table reports estimates from two different model specifications (baseline and preferred), that differ as the preferred specification allows for heterogeneous effects based on pre-treatment numeracy. Consistently with the randomization design, all regression include area fixed effects. *Numeracy* is the standardized numeracy score based on PIAAC test.The indicator is standardized with respect to the 105 applicants to LEDA. Robust standard errors in parentheses. Legend: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Main Tables - Alternative definition of the treatment

This section presents the results using an alternative definition of take-up based on actual participation. In the absence of attendance data, we employ a more restrictive measure, namely a binary indicator that takes the value 1 in case students completed at least one of the four LEDA exams by early June 2023 and zero otherwise. Even if the first stage decreases (see estimates in Table B.1 versus estimates in Table A.3 for the baseline model without heterogeneous effects and estimates in Table B.2 versus those reported in Table A.4 for the preferred model that allows heterogeneous effects), the instrument is not weak and we have sufficient independent sources of variation to identify parameters in the model with heterogeneous effects. As expected, the causal effect of actual participation (as proxied by taking at least one exam) has a larger effect than the mere enrollment leading to an increase in data literacy of over 0.5, nearly double the effect observed when considering the causal effect of enrollment. Additionally, heterogeneity by pre-treatment numeracy level is more pronounced: the causal effect of LEDA for students with low levels of numeracy is more pronounced, while the causal effect for students with high levels of numeracy is not statistically significant and close to zero in absolute value.[1] For completeness, Table B.3, Table B.4, Table B.5, Table B.6, Table B.7, Table B.8 report both ITT and IV results, even if ITT estimates coincide with those previously reported in Table A.5, Table A.6, Tab A.6, Table A.7, Table A.8, Table A.9, Table A.10.

[1]We refer to students with low levels of numeracy as those with pre-treatment levels of numeracy 1sd below average and to students with hight levels of numeracy as those with pre-treatment levels of numeracy 1sd above average.

Table B.1: Effect of being offered a slot for the LEDA program on participation (First Stage)

	No controls	Pre-treatment controls
	(1)	(2)
Assigned to LEDA	0.424***	0.422***
	(0.079)	(0.081)
Numeracy		-0.008
		(0.043)
Academic		0.081
High School		(0.091)
Female		-0.096
		(0.100)
Area fe	Yes	Yes
F-test	28.655	27.006
Adj. R-Square	0.232	0.221
Observations	85	85

Note: The table reports estimate of first stage parameters assessing the causal effect of being offered a slot for LEDA on participation to the program using linear probability model and OLS estimator for alternative specifications that differ for the control variables included on the sample of applicants who completed the endline survey. Our preferred specification is the one presented in column (2). IV estimates corresponding to specification in column (2) are presented in Table B.3 (data literacy) and Table B.4 and B.5 (students' main careers). Binary indicator for participation into LEDA is having taken at least one exam by the end of the first exam session (vs having taken none). Consistently with the randomization design, all regression include area fixed effects. *Numeracy* is the standardized numeracy score based on PIAAC test. The indicator is standardized with respect to the 105 applicants to LEDA. Robust standard errors in parentheses. Legend: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2: Effect of being offered a slot for the LEDA program on participation (First Stage) - Models allowing for heterogenous effects by pre-treatment numeracy levels

	Enrollment (P)	
	P	P · Numeracy
Assigned LEDA	0.423***	-0.045
	(0.081)	(0.066)
Assigned LEDA · Numeracy	-0.039	0.324***
	(0.081)	(0.099)
Numeracy	0.010	-0.011
	(0.028)	(0.022)
Area fe	Yes	Yes
F-test	13.526	5.704
SW F-test	25.798	10.197
Observations	85	85

Note: The table reports estimate of first stage parameters assessing the causal effect of being offered a slot for LEDA on participation to the program using linear probability model and OLS estimator in a model were heterogeneous effects are allowed (see Tables B.3 for corresponding IV estimates on data literacy and Table B.4 for students' careers). The sample for the analysis includes applicants who completed the endline survey. Binary indicator for participation into LEDA is having taken at least one exam by the end of the first exam session (vs having taken none) and it is denoted with P. Consistently with the randomization design, all regression include area fixed effects. *Numeracy* is the standardized numeracy score based on PIAAC test. The indicator is standardized with respect to the 105 applicants to LEDA. P is the participation indicator, either based on enrollment or on exams. Legend: SW for Sanderson-Windmeijer multivariate F test of excluded instruments. The SW complement the F-test on joint significance of the instrument as they are tests for under-identification and weak identification of individual endogenous regressors in models with multiple endogenous regressors and instruments. They check for "sufficient" independent source of variation, *partialling-out* linear projections of the remaining endogenous regressors. Robust standard errors in parentheses. Legend: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: Effect of the assignment and of participation to the LEDA program on data literacy- ITT and IV results. Measure of participation based on: at least one exam taken by the end of the exam session

	Model parameters' estimates			
	Baseline specification		Preferred specification	
	ITT	IV	ITT	IV
Assigned to LEDA	0.227		0.232	
	(0.175)		(0.174)	
Assigned to LEDA · Numeracy			-0.197	
			(0.147)	
LEDA Participant		0.538		0.490
		(0.404)		(0.411)
LEDA Participant · Numeracy				-0.549
				(0.454)
Numeracy	0.447***	0.451***	0.539***	0.540***
	(0.077)	(0.074)	(0.106)	(0.103)
Area fe	Yes	Yes	Yes	Yes
Observations	85	85	85	85
Assigned to LEDA (ITT)				
@**Low Numeracy** (-1sd) [m.e.]			**0.429***	
2-sided p-value (H_1 : m.effect $\neq 0$)			0.079	
@**High Numeracy** (+1sd) [m.e.]			**0.035**	
2-sided p-value (H_1 : m.effect $\neq 0$)			0.871	
LEDA **Participant** (IV)				
@**Low Numeracy** (-1sd) [m.e.]				**1.039***
2-sided p-value (H_1 : m.effect $\neq 0$)				0. 094
@**High Numeracy** (+1sd) [m.e.]				**-0.059**
2-sided p-value (H_1 : m.effect $\neq 0$)				0.922

Note: The table reports results on independent regression assessing: i) the causal effect of being offered a slot for LEDA on data literacy (ITT); i) the causal effect of participation to LEDA on data literacy (IV). See Table B.1 and Table B.2 for corresponding first stage estimates. The sample for the analysis includes applicants who completed the endline survey. Binary indicator for participation into LEDA is enrollment in the program (vs not enrollment). The Table reports estimates from two different model specifications (baseline and preferred), that differ as the preferred specification allows for heterogeneous effects based on pre-treatment numeracy Consistently with the randomization design, all regression include area fixed effects. *Numeracy* is the standardized numeracy score based on PIAAC test. The indicator is standardized with respect to the 105 applicants to LEDA. Robust standard errors in parentheses. Legend: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: Effect of the assignment and of participation to the LEDA program on primary University career (number of exams) - ITT and IV results. Measure of participation based on: at least one exam taken by the end of the exam session

	Model parameters' estimates			
	Baseline specification		Preferred specification	
	ITT	IV	ITT	IV
Assigned to LEDA	-0.079		-0.053	
	(0.645)		(0.641)	
Assigned to LEDA · Numeracy			-0.977	
			(0.612)	
LEDA Participant		-0.187		0.345
		(1.458)		(1.513)
LEDA Participant · Numeracy				-3.065
				(1.899)
Numeracy	0.530*	0.528*	0.988**	1.025***
	(0.291)	(0.277)	(0.388)	(0.383)
Academic	-1.701*	-1.686***	-1.860***	-2.277***
High School	(0.653)	(0.607)	(0.624)	(0.674)
Female	0.418	0.400	0.309	-0.140
	(0.754)	(0.690)	(0.762)	(0.766)
Area fe	Yes	Yes	Yes	Yes
Observations	85	85	85	85
Assigned to LEDA (ITT)				
@**Low Numeracy** (-1sd) [m.e.]			**0.924**	
2-sided p-value (H_1 : m.effect $\neq 0$)			0.329	
@**High Numeracy** (+1sd) [m.e.]			**-1.030**	
2-sided p-value (H_1 : m.effect $\neq 0$)			0.217	
LEDA **Participant** (IV)				
@**Low Numeracy** (-1sd) [m.e.]				**2.610**
2-sided p-value (H_1 : m.effect $\neq 0$)				0.221
@**High Numeracy** (+1sd) [m.e.]				**-3.520**
2-sided p-value (H_1 : m.effect $\neq 0$)				0.195

Note: The table reports results on independent regression assessing: i) the causal effect of being offered a slot for LEDA on main University career (number of exam passed after LEDA program activities start) (ITT); i) the causal effect of participation to LEDA on main University career (number of graded exam passed after LEDA program activities start) (see Table B.1 and Table B.2 for corresponding first stage estimates). The sample for the analysis includes applicants who completed the endline survey. Binary indicator for participation into LEDA is enrollment in the program (vs not enrollment). The Table reports estimates from two different model specifications (baseline and preferred), that differ as the preferred specification allows for heterogeneous effects based on pre-treatment numeracy Consistently with the randomization design, all regression include area fixed effects.*Numeracy* is the standardized numeracy score based on PIAAC test. The indicator is standardized with respect to the 105 applicants to LEDA. Robust standard errors in parentheses. Legend: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.5: Effect of the assignment and of participation to the LEDA program on primary University career (GPA)- ITT and IV results. Measure of participation based on: at least one exam taken by the end of the exam session

	Model parameters' estimates			
	Baseline specification		Preferred specification	
	ITT	IV	ITT	IV
Assigned to LEDA	0.148		0.158	
	(0.202)		(0.197)	
Assigned to LEDA · Numeracy			-0.463**	
			(0.183)	
LEDA Participant		0.330		0.263
		(0.432)		(0.484)
LEDA Participant · Numeracy				-1.097*
				(0.608)
Numeracy	0.117	0.114	0.309**	0.292**
	(0.091)	(0.088)	(0.127)	(0.122)
Area fe	Yes	Yes	Yes	Yes
Observations	85	85	85	85
Assigned to LEDA (ITT)				
@**Low Numeracy** (-1sd) [m.e.]			**0.622****	
2-sided p-value (H_1 : m.effect $\neq 0$)			0.024	
@**High Numeracy** (+1sd) [m.e.]			**-0.305**	
2-sided p-value (H_1 : m.effect $\neq 0$)			0.259	
LEDA **Participant** (IV)				
@**Low Numeracy** (-1sd) [m.e.]				**1.361***
2-sided p-value (H_1 : m.effect $\neq 0$)				0.053
@**High Numeracy** (+1sd) [m.e.]				**-0.834**
2-sided p-value (H_1 : m.effect $\neq 0$)				0.323

Note: The table reports results on independent regression assessing: i) the causal effect of being offered a slot for LEDA on GPA in the main University career (ITT); i) the causal effect of participation to LEDA on on GPA in the main University career (see Table B.1 and Table B.2 for corresponding first stage estimates). The sample for the analysis includes applicants who completed the endline survey. Binary indicator for participation into LEDA is enrollment in the program (vs not enrollment). The Table reports estimates from two different model specifications (baseline and preferred), that differ as the preferred specification allows for heterogeneous effects based on pre-treatment numeracy Consistently with the randomization design, all regression include area fixed effects.*Numeracy* is the standardized numeracy score based on PIAAC test. The indicator is standardized with respect to the 105 applicants to LEDA. Robust standard errors in parentheses. Legend: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.6: Effect of the assignment and of participation to the LEDA program on primary university career, outcome: Graduated (Master, main career), self-reported in November 2025. ITT and IV results. Measure of participation based on: at least one exam taken by the end of the first exam session. Sample: all follow-up respondents

	Model parameters' estimates			
	Baseline specification		Preferred specification	
	ITT	IV	ITT	IV
Assigned to LEDA	0.010		0.011	
	(0.085)		(0.085)	
Assigned to LEDA · Numeracy			-0.062	
			(0.075)	
LEDA Participant		0.026		-0.007
		(0.207)		(0.220)
LEDA Participant · Numeracy				-0.176
				(0.218)
Numeracy	0.022	0.023	-0.012	0.013
	(0.064)	(0.063)	(0.064)	(0.061)
Area fe	Yes	Yes	Yes	Yes
N	93	93	93	93
	Hypothesis testing (p-values)			
Assigned to LEDA (ITT)				
@**Low Numeracy** (-1sd) [m.e.]			**0.073**	
2-sided p-value (H_1: m.effect $\neq 0$)			0.563	
@**High Numeracy** (+1sd) [m.e.]			**-0.050**	
2-sided p-value (H_1: m.effect $\neq 0$)			0.617	
LEDA **Participant** (IV)				
@**Low Numeracy** (-1sd) [m.e.]				**0.169**
2-sided p-value (H_1: m.effect $\neq 0$)				0.502
@**High Numeracy** (+1sd) [m.e.]				**-0.183**
2-sided p-value (H_1: m.effect $\neq 0$)				0.609

Note: The table reports results on independent regression assessing: i) the causal effect of being offered a slot for LEDA on regular University career (ITT); ii) the causal effect of participation to LEDA on regular University career measured as the probability of graduating within about two years since the end of the LEDA program (IV). See Table **??** and Table **??** for corresponding first stage estimates. The sample for the analysis includes applicants who the follow-up survey regardless whether they also completed the endline survey. Binary indicator for participation into LEDA is having taken at least one exam by the end of the first exam session (vs having taken none). The Table reports estimates from two different model specifications (baseline and preferred), that differ as the preferred specification allows for heterogeneous effects based on pre-treatment numeracy. Consistently with the randomization design, all regression include area fixed effects. *Numeracy* is the standardized numeracy score based on PIAAC test. The indicator is standardized with respect to the 105 applicants to LEDA. Robust standard errors in parentheses. Legend: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.7: Effect of the assignment and of participation to the LEDA program on on primary university career, outcome: Paid occupation, self-reported in November 2025 - ITT and IV results. Measure of participation based on: at least one exam taken by the end of the first exam session. Sample: all follow-up respondents

	Model parameters' estimates			
	Baseline specification		Preferred specification	
	ITT	IV	ITT	IV
Assigned to LEDA	0.078		0.080	
	(0.086)		(0.085)	
Assigned to LEDA · Numeracy			-0.136*	
			(0.077)	
LEDA Participant		0.198		0.133
		(0.210)		(0.243)
LEDA Participant · Numeracy				-0.348
				(0.272)
Numeracy	-0.037	-0.032	0.028	0.023
	(0.039)	(0.039)	(0.052)	(0.050)
Area fe	Yes	Yes	Yes	Yes
N	93	93	93	93
	Hypothesis testing (p-values)			
Assigned to LEDA (ITT)				
@**Low Numeracy** (-1sd) [m.e.]			**0.216****	
2-sided p-value (H_1: m.effect $\neq 0$)			0.048	
@**High Numeracy** (+1sd) [m.e.]			**-0.056**	
2-sided p-value (H_1: m.effect $\neq 0$)			0.645	
LEDA **Participant** (IV)				
@**Low Numeracy** (-1sd) [m.e.]				**0.481***
2-sided p-value (H_1: m.effect $\neq 0$)				0.059
@**High Numeracy** (+1sd) [m.e.]				**-0.215**
2-sided p-value (H_1: m.effect $\neq 0$)				0.632

Note: The table reports results on independent regression assessing: i) the causal effect of being offered a slot for LEDA on on the probability of being in paid work within about two years since the end of the LEDA program (ITT); ii) the causal effect of participation to LEDA on the probability of being in paid work within about two years since the end of the LEDA program (IV). See Table ?? and Table ?? for corresponding first stage estimates. The sample for the analysis includes applicants who the follow-up survey regardless whether they also completed the endline survey. Binary indicator for participation into LEDA is having taken at least one exam by the end of the first exam session (vs having taken none). The Table reports estimates from two different model specifications (baseline and preferred), that differ as the preferred specification allows for heterogeneous effects based on pre-treatment numeracy. Consistently with the randomization design, all regression include area fixed effects. *Numeracy* is the standardized numeracy score based on PIAAC test. The indicator is standardized with respect to the 105 applicants to LEDA. Robust standard errors in parentheses. Legend: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.8: Effect of the assignment and of participation to the LEDA program on primary university career, outcome: looking for a job, self-reported in November 2025. ITT and IV results. Measure of participation based on: enrollment. Sample: all follow-up respondents

	Model parameters' estimates			
	Baseline specification		Preferred specification	
	ITT	IV	ITT	IV
Assigned to LEDA	-0.093		-0.094	
	(0.073)		(0.073)	
Assigned to LEDA · Numeracy			0.094	
			(0.070)	
LEDA Participant		-0.235		-0.196
		(0.183)		(0.203)
LEDA Participant · Numeracy				0.212
				(0.227)
Numeracy	0.030	0.024	-0.015	-0.010
	(0.033)	(0.031)	(0.048)	(0.046)
Area fe	Yes	Yes	Yes	Yes
N	93	93	93	93
	Hypothesis testing (p-values)			
Assigned to LEDA (ITT)				
@**Low Numeracy** (-1sd) [m.e.]			**-0.188***	
2-sided p-value (H_1: m.effect $\neq 0$)			0.055	
@**High Numeracy** (+1sd) [m.e.]			**-0.000**	
2-sided p-value (H_1: m.effect $\neq 0$)			0.997	
LEDA **Participant** (IV)				
@**Low Numeracy** (-1sd) [m.e.]				**-0.408***
2-sided p-value (H_1: m.effect $\neq 0$)				0.070
@**High Numeracy** (+1sd) [m.e.]				**0.016**
2-sided p-value (H_1: m.effect $\neq 0$)				0.964

Note: The table reports results on independent regression assessing: i) the causal effect of being offered a slot for LEDA on the job search within about two years since the end of the LEDA program (self-reported) (ITT); ii) the causal effect of participation to LEDA on the probability of being on the job search within about two years since the end of the LEDA program (self-reported) (IV). See Table **??** and Table **??** for corresponding first stage estimates. The sample for the analysis includes applicants who the follow-up survey regardless whether they also completed the endline survey. Binary indicator for participation into LEDA is having taken at least one exam by the end of the first exam session (vs having taken none). The Table reports estimates from two different model specifications (baseline and preferred), that differ as the preferred specification allows for heterogeneous effects based on pre-treatment numeracy. Consistently with the randomization design, all regression include area fixed effects. *Numeracy* is the standardized numeracy score based on PIAAC test. The indicator is standardized with respect to the 105 applicants to LEDA. Robust standard errors in parentheses. Legend: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Follow-up key variables and questions

This section describes the construction of the main follow-up outcomes, based on the survey administered approximately two years after the completion of the LEDA program. The survey collects information on educational attainment, labor market status, and expectations about future career prospects of respondents.

We first construct a binary indicator for **graduation**, equal to one if the respondent reports having completed their Master's degree at the time of the survey (i.e., selecting "Yes" to the relevant question), and zero otherwise.

We then derive two indicators capturing current labor market status. The variable **paid occupation** is a binary indicator equal to one if the respondent reports being engaged in a remunerated activity. This includes both standard employment and paid doctoral studies. Operationally, this variable takes the value one if the respondent selects "Working (paid employment)" in response to the question *"What is your current main occupation?"*, or if the respondent selects "tertiary-level training, including paid positions (e.g., PhD programs)" and reports receiving remuneration—either sufficient or partially sufficient to cover monthly expenses—in response to the question: *"Is this a paid position? (e.g., PhD scholarship)"*.

In addition, we define an indicator for **job search**, equal to one if the respondent declares being currently unemployed and actively looking for a job (i.e., selecting "Looking for a job" in the question: *"What is your current main occupation?*

The survey also collects the expectations of the respondents about the **relevance of quantitative skills** in their future careers. In particular, individuals are asked to assess the importance of data literacy and analytical thinking in their future occupation, five years after the survey rating the statement *"Please consider your expected professional situation five years from now. Indicate how important you believe each skill will be for your future career."* Questions are measured on a 0 (not important) - 100 (of utmost importance) scale, with 50 anchored as "important". Based on these responses, we constructed a **composite index** of **perceived importance of analytical skills**. Each component is first standardized using the mean and standard deviation of the non-assigned group participating in the follow-up assessment. We then compute the average of the two standardized components and re-standardize the resulting index using the same reference group. As a result, the index is expressed in standard deviation units relative to the control group, with mean zero and unit variance among non-assigned individuals.

Finally, we collect information on the **future career expectations** of the respondents. Individuals rate their agreement with statements on expected earning potential and opportunities for professional growth five years ahead: *"In five years I will have good earning potential" and "In five years I will have good opportunities for professional growth"*. Questions are measured using a scale from 0 ("do not agree at all") to 100 ("fully agree"), with 50 corresponding to a neutral position.