# Machine learning and effectiveness of financial education programs

Ginevra Buratti & Alessio D'Ignazio

**Bank of Italy**

International Conference on Financial Fragility and Financial education of Households and Firms - Urbino, 8-9 june 2023

# Disclaimer

The views expressed in the slides are those of the presenter only and should not be attributed to the Bank of Italy or the Eurosystem.

# Financial education programs

- Households and entrepreneurs with low financial literacy make poor decisions $\rightarrow$ negative impact on both their financial welfare and that of the whole society
- The effectiveness of financial education programs may be undermined by: low participation, poor execution, suboptimal design or inappropriate audience. In this paper, we focus on the latter issue

# This paper

- We study whether algorithms could improve the effectiveness of financial education programs, by identifying ex-ante the most appropriate recipients (i.e., those who need FE the most). Two steps:

1. We exploit data gathered from a sample of individuals and devise an algorithm to identify appropriate recipients of FE programs
2. We simulate a policy scenario. We apply the algorithm to a new group of individuals and:
    - individuate those who should be offered a financial education course (targeted individuals) and those who should not (not-targeted)
    - evaluate whether the effectiveness of a financial education course is different among these two groups

# Data: The financial education campaign by Edufin Committee

- We use individual data from about 3,800 individuals who participated to a financial education campaign run by Edufin Committee in 2021.
- Financial education was taught by means of three TV programs ("treatments"):

  1. TV-show L'Eredita
  2. soap opera Un posto al sole (UPAS)
  3. various media messages (Sofia)

- The campaign was paired by a randomized experiment (RCT) to assess its effectiveness: the sample was equally divided in four groups: T1 (UPAS), T2 (L'Eredita), T3 (Sofia), control group.

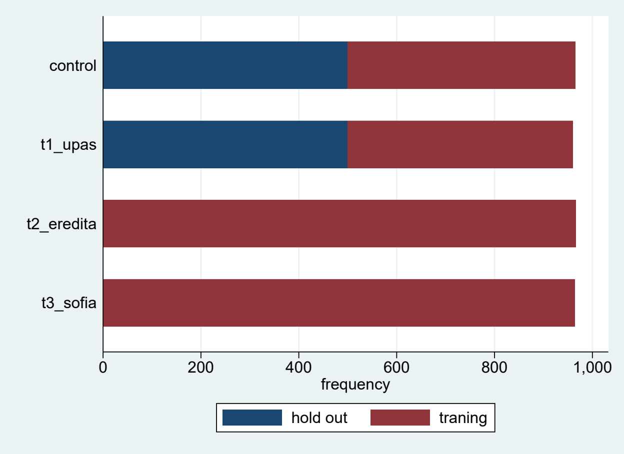
# Data: The financial education campaign by Edufin Committee (cont.)

- All four groups of individuals were administered a questionnaire before the treatment (pre-test) and a questionnaire after the treatment (post-test)
    - The questionnaires included a series of questions on financial topics, as well as a section on individual characteristics
- Treated individuals' compliance to the RCT was assessed by asking them few questions after each TV-episode
- To incentivize individuals to participate to the RCT, a small monetary prize was provided

# By the way...

# Training vs hold-out sample

Sample conditionally random split: training and hold-out



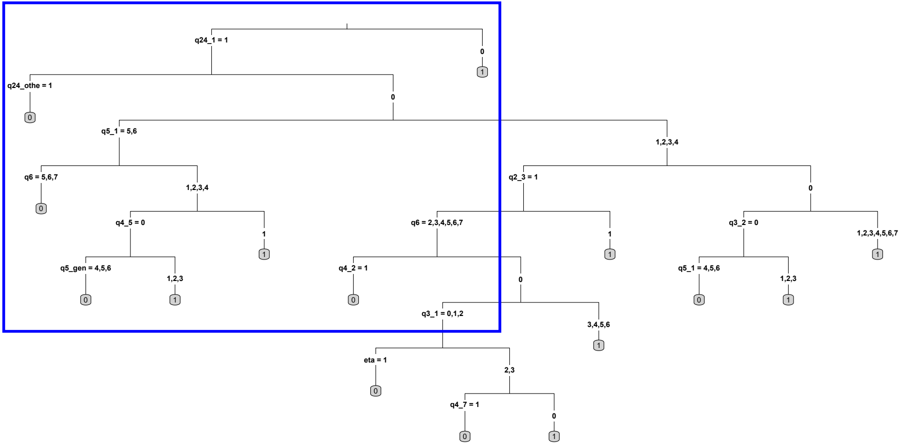

Notes: units.

# Financial education targeting algorithm (machine learning)

- We use training sample's pre-test data only (i.e. red parts of the above fig.)
- Set up an algorithm that predicts individuals who fail at least two out of four questions about topics covered by UPAS
- We employ machine learning (ML) tools (trees, RF), with the set of predictors being easily observable variables:

<table>
<tr><td>sex</td><td>age</td><td>q3_1 no. children</td><td>q3_2 no. adults</td></tr>
<tr><td colspan="2">q2_1–q2_6 civil status</td><td colspan="2">q4_1–q4_7 occupational status</td></tr>
<tr><td colspan="2">q5_1 level of education</td><td colspan="2">q5_gen parents' level of education</td></tr>
<tr><td colspan="2">q24_1 bank account</td><td colspan="2">q24_other other financial instruments</td></tr>
<tr><td colspan="2">q6 income band</td><td colspan="2">q7_1–q7_4 area</td></tr>
</table>

# The ML-based targeting rule (ML: tree)




zoom

# Policy scenario simulation

- We apply the ML algorithm-based rule to a new set of individuals (i.e., "blue" guys)
- Very importantly, for such individuals we observe their financial literacy (measured by means of the two questionnaires) both before and after the financial education campaign
- We estimate the impact of the financial education campaign and assess whether it is different between target and not-target individuals

# Treated vs Control individuals

- Despite the monetary prize, individuals assigned to treatment (i.e., watch UPAS) could fail to comply (cheating...)
- To tackles this problem we exploit data on which TV-programs people usually watch (including UPAS)
- Treated individuals: assigned to "watch UPAS" group & claim to usually watch UPAS (stricter def: & correctly answers most "check" questions)
- Control individuals: assigned to control group & claim not to usually watch UPAS

# Baseline results

| | Full sample | ML: Random forest target | ML: Random forest not target |
|---|---|---|---|
| **panel (a): y = binary (improvement) indicator** | | | |
| **Type I treated** | 0.0709 | 0.135* | -0.0206 |
| | (0.0527) | (0.0713) | (0.0744) |
| Observations | 602 | 302 | 300 |
| **Type II treated** | 0.0917 | 0.170* | -0.00986 |
| | (0.0638) | (0.0868) | (0.0899) |
| Observations | 562 | 280 | 282 |
| **panel (b): y = pre-post score difference** | | | |
| **Type I treated** | 0.0802 | 0.551* | -0.545 |
| | (0.244) | (0.333) | (0.338) |
| Observations | 602 | 302 | 300 |
| **Type II treated** | 0.311 | 0.901** | -0.415 |
| | (0.295) | (0.405) | (0.405) |
| Observations | 562 | 280 | 282 |

**Notes:** Holdout sample. OLS regressions. Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

# Robustness 1: crtls

| | Full sample | ML: Random forest target | ML: Random forest not target |
|---|---|---|---|
| **panel (a): y = binary (improvement) indicator** | | | |
| VARIABLES | | target | not target |
| **Type I treated** | 0.0777* | 0.137** | 0.0254 |
| | (0.0456) | (0.0613) | (0.0716) |
| Observations | 602 | 302 | 300 |
| **Type II treated** | 0.0632 | 0.142* | 0.0252 |
| | (0.0560) | (0.0751) | (0.0877) |
| Observations | 562 | 280 | 282 |
| **panel (b): y = pre-post score difference** | | | |
| **Type I treated** | 0.141 | 0.607** | -0.323 |
| | (0.197) | (0.270) | (0.294) |
| Observations | 602 | 302 | 300 |
| **Type II treated** | 0.184 | 0.724** | -0.255 |
| | (0.233) | (0.324) | (0.334) |
| Observations | 562 | 280 | 282 |

**Notes**: Holdout sample. OLS regressions. Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. (1) control variables included: see Table 9

# Additional exercises

1. Repeat estimates of 100 different training vs hold-out sample splits
   figure
2. Falsification test table
3. Balancing tests table b1 table b2 table b3 table b4

# Conclusions

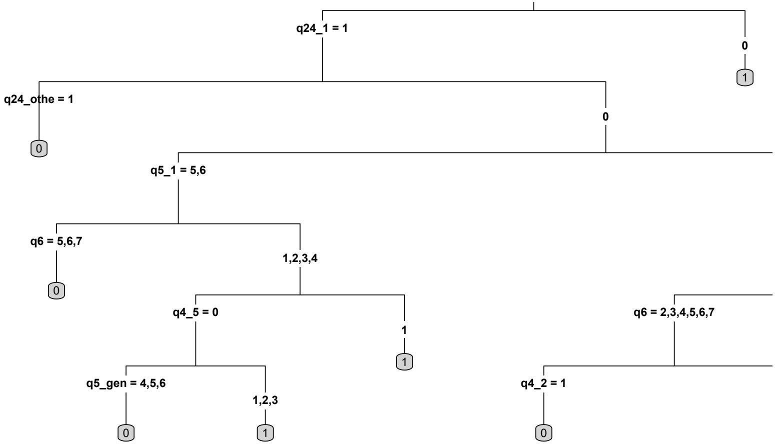
1. We show that ML-based targeting can improve the effectiveness of a financial education campaign by helping identify ex-ante the most appropriate recipients

2. This approach can be widely applied. ML targeting could apply as well to schools, teachers, students

3. Further issues: transparency & external validity

Thank you!

# The ML-based targeting rule (ML: tree): zoom




back

# Falsification test results

| | Full sample | ML: target | ML: not target | Full sample | ML: target | ML: not target |
|---|---|---|---|---|---|---|
| | y = binary (improv.) indicator | | | y = pre-post score difference | | |
| **T. I treat.** | -0.0147 | -0.0142 | -0.0317 | 0.0850 | -0.0107 | 0.106 |
| | (0.0522) | (0.0728) | (0.0719) | (0.235) | (0.293) | (0.365) |
| Obs. | 602 | 302 | 300 | 602 | 302 | 300 |
| **T. II treat.** | 0.0528 | 0.126 | -0.0424 | 0.429 | 0.578 | 0.190 |
| | (0.0639) | (0.0851) | (0.0858) | (0.293) | (0.354) | (0.446) |
| Obs. | 562 | 280 | 282 | 562 | 280 | 282 |

**Notes**: Holdout sample. OLS regressions. Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

back

# 100 different training vs hold-out sample splits. Results

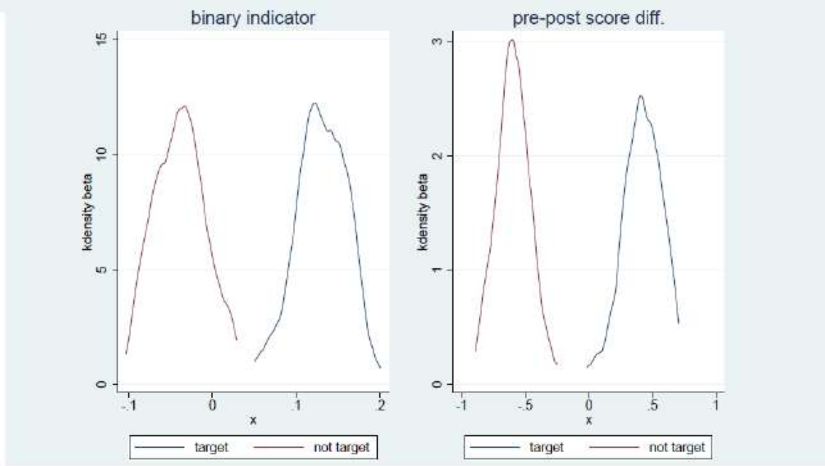



Figure 13: Treatment effect estimates (type I treated) for target and non target groups
**Notes:** Distribution of beta estimated on 100 random training vs holdout samples.

# Balancing test: type I treated, ML-target

Table 9: ML-targeted individuals in the holdout sample: type I treated, treated vs control balancing tests

| | treated | | control | | diff. of means | |
|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | b | p |
| score_pre | 2.528 | 1.695 | 2.531 | 1.659 | 0.003 | (0.988) |
| big_3_mistakes | 0.167 | 0.375 | 0.199 | 0.400 | 0.033 | (0.523) |
| female | 0.625 | 0.488 | 0.551 | 0.498 | -0.074 | (0.258) |
| older | 0.472 | 0.503 | 0.352 | 0.478 | -0.121 | (0.072) |
| graduate | 0.167 | 0.375 | 0.180 | 0.385 | 0.013 | (0.796) |
| perm_empl | 0.375 | 0.488 | 0.309 | 0.463 | -0.066 | (0.304) |
| low_income | 0.264 | 0.444 | 0.270 | 0.445 | 0.006 | (0.924) |
| fl_autoperc_low | 0.486 | 0.503 | 0.516 | 0.501 | 0.030 | (0.661) |
| married | 0.639 | 0.484 | 0.555 | 0.498 | -0.084 | (0.197) |
| family_memb_lt18 | 0.542 | 0.502 | 0.555 | 0.498 | 0.013 | (0.846) |
| south_islands | 0.403 | 0.494 | 0.375 | 0.485 | -0.028 | (0.673) |
| part_fe_courses | 0.278 | 0.451 | 0.211 | 0.409 | -0.067 | (0.260) |
| make_ends_meet_diff | 0.528 | 0.503 | 0.488 | 0.501 | -0.039 | (0.557) |
| info_web | 0.458 | 0.502 | 0.512 | 0.501 | 0.053 | (0.427) |
| info_fin_web | 0.361 | 0.484 | 0.414 | 0.494 | 0.053 | (0.416) |
| newspapers | 0.431 | 0.499 | 0.324 | 0.469 | -0.106 | (0.108) |
| Observations | 72 | | 256 | | 328 | |

**Notes**: Holdout sample, ML-targeted individuals. t-tests on the equality of means for treated and control individuals, assuming unequal variances. Variables are described in Table 2. Type I treated individuals are considered. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

back

# Balancing test: type I treated, not ML-target

Table 10: Not ML-targeted individuals in the holdout sample: type I treated, treated vs control balancing tests

| | treated | | control | | diff. of means | |
|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | b | p |
| score_pre | 3.789 | 1.094 | 3.644 | 1.288 | -0.145 | (0.462) |
| big_3_mistakes | 0.105 | 0.311 | 0.076 | 0.266 | -0.029 | (0.589) |
| female | 0.553 | 0.504 | 0.534 | 0.500 | -0.019 | (0.832) |
| older | 0.421 | 0.500 | 0.424 | 0.495 | 0.003 | (0.976) |
| graduate | 0.579 | 0.500 | 0.547 | 0.499 | -0.032 | (0.713) |
| perm_empl | 0.474 | 0.506 | 0.479 | 0.501 | 0.005 | (0.954) |
| low_income | 0.053 | 0.226 | 0.064 | 0.244 | 0.011 | (0.786) |
| fl_autoperc_low | 0.211 | 0.413 | 0.263 | 0.441 | 0.052 | (0.477) |
| married | 0.737 | 0.446 | 0.623 | 0.486 | -0.114 | (0.155) |
| family_memb_lt18 | 0.447 | 0.504 | 0.534 | 0.500 | 0.087 | (0.330) |
| south_islands | 0.368 | 0.489 | 0.369 | 0.483 | 0.000 | (0.998) |
| part_fe_courses | 0.395 | 0.495 | 0.398 | 0.491 | 0.004 | (0.967) |
| make_ends_meet_diff | 0.211 | 0.413 | 0.25 | 0.434 | 0.039 | (0.590) |
| info_web | 0.605 | 0.495 | 0.746 | 0.436 | 0.140 | (0.106) |
| info_fin_web | 0.658 | 0.481 | 0.657 | 0.476 | -0.001 | (0.989) |
| newspapers | 0.605 | 0.495 | 0.445 | 0.498 | -0.160 | (0.070) |
| Observations | 38 | | 236 | | 274 | |

**Notes:** Holdout sample, not ML-targeted individuals. t-tests on the equality of means for treated and control individuals, assuming unequal variances. Variables are described in Table 2. Type I treated individuals are considered. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

back

# Balancing test: type II treated, ML-target

Table 11: ML-targeted individuals in the holdout sample: type II treated, treated vs control balancing tests

| | treated | | control | | diff. of means | |
|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | b | p |
| score_pre | 2.283 | 1.772 | 2.531 | 1.659 | 0.249 | (0.380) |
| big_3_mistakes | 0.174 | 0.383 | 0.199 | 0.400 | 0.025 | (0.684) |
| female | 0.674 | 0.474 | 0.551 | 0.498 | -0.123 | (0.112) |
| older | 0.413 | 0.498 | 0.352 | 0.478 | -0.061 | (0.441) |
| graduate | 0.196 | 0.401 | 0.18 | 0.385 | -0.016 | (0.803) |
| perm_empl | 0.283 | 0.455 | 0.309 | 0.463 | 0.026 | (0.723) |
| low_income | 0.304 | 0.465 | 0.27 | 0.445 | -0.035 | (0.640) |
| fl_autoperc_low | 0.522 | 0.505 | 0.516 | 0.501 | -0.006 | (0.940) |
| married | 0.674 | 0.474 | 0.555 | 0.498 | -0.119 | (0.124) |
| family_memb_lt18 | 0.500 | 0.506 | 0.555 | 0.498 | 0.055 | (0.501) |
| south_islands | 0.326 | 0.474 | 0.375 | 0.485 | 0.049 | (0.523) |
| part_fe_courses | 0.261 | 0.444 | 0.211 | 0.409 | -0.05 | (0.480) |
| make_ends_meet_diff | 0.543 | 0.504 | 0.488 | 0.501 | -0.055 | (0.496) |
| info_web | 0.478 | 0.505 | 0.512 | 0.501 | 0.033 | (0.680) |
| info_fin_web | 0.348 | 0.482 | 0.414 | 0.494 | 0.066 | (0.395) |
| newspapers | 0.478 | 0.505 | 0.324 | 0.469 | -0.154 | (0.059) |
| Observations | 46 | | 256 | | 302 | |

**Notes**: Holdout sample, ML-targeted individuals. t-tests on the equality of means for treated and control individuals, assuming unequal variances. Variables are described in Table 2. Type II treated individuals are considered. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

back

# Balancing test: type II treated, not ML-target

Table 12: Not ML-targeted individuals in the holdout sample: type II treated, treated vs control balancing tests

| | treated | | control | | diff. of means | |
|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | b | p |
| score_pre | 3.708 | 1.197 | 3.644 | 1.288 | -0.064 | (0.805) |
| big_3_mistakes | 0.125 | 0.338 | 0.076 | 0.266 | -0.049 | (0.499) |
| female | 0.417 | 0.504 | 0.534 | 0.500 | 0.117 | (0.286) |
| older | 0.417 | 0.504 | 0.424 | 0.495 | 0.007 | (0.948) |
| graduate | 0.625 | 0.495 | 0.547 | 0.499 | -0.078 | (0.466) |
| perm_empl | 0.500 | 0.511 | 0.479 | 0.501 | -0.021 | (0.848) |
| low_income | 0.042 | 0.204 | 0.064 | 0.244 | 0.022 | (0.627) |
| fl_autoperc_low | 0.292 | 0.464 | 0.263 | 0.441 | -0.029 | (0.772) |
| married | 0.708 | 0.464 | 0.623 | 0.486 | -0.085 | (0.400) |
| family_memb_lt18 | 0.417 | 0.504 | 0.534 | 0.500 | 0.117 | (0.286) |
| south_islands | 0.542 | 0.509 | 0.369 | 0.483 | -0.173 | (0.122) |
| part_fe_courses | 0.417 | 0.504 | 0.398 | 0.491 | -0.018 | (0.866) |
| make_ends_meet_diff | 0.250 | 0.442 | 0.25 | 0.434 | 0.000 | (1.00) |
| info_web | 0.667 | 0.482 | 0.746 | 0.436 | 0.079 | (0.446) |
| info_fin_web | 0.708 | 0.464 | 0.657 | 0.476 | -0.052 | (0.609) |
| newspapers | 0.542 | 0.509 | 0.445 | 0.498 | -0.097 | (0.382) |
| Observations | 24 | | 236 | | 260 | |

**Notes:** Holdout sample, not ML-targeted individuals. t-tests on the equality of means for treated and control individuals, assuming unequal variances. Variables are described in Table 2. Type II treated individuals are considered. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

back