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THE USE OF ROBO-ADVISORS IN ITALY: INSIGHTS FROM A NEW SURVEY

by Massimiliano Stacchini* and Pietro Vassallo*

Abstract

Robo-advisors, the provision of (affordable) financial advice through algorithms on digital platforms, offer great potential to increase participation in financial markets by private individuals. However, like any innovation in finance, opportunities also come with challenges. Based on data from a recent survey of 5,000 individuals, we conduct an in-depth analysis of the characteristics of individuals who use robo-advisors in a country such as Italy, where participation in financial markets is traditionally low, and assess the influence of this technology on the general public's propensity to make financial investments. Our results show that (i) the adoption of robo-advisors is higher among individuals with greater digital skills but limited financial knowledge; (ii) the adoption of robo-advisors positively influences the propensity to purchase financial assets, such as stocks, bonds, and investment funds.

JEL Classification: D14, G53, O33.

Keywords: fintech innovation, financial knowledge, household finance.

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1 Motivation and main findings[1]

People are called upon every day to make financial decisions that impact their financial well-being: choosing between savings accounts, deciding on investments in stocks or bonds, or planning for retirement. The availability of financial tools to participate in financial markets is growing rapidly, but many individuals remain reluctant to view financial markets as an investment opportunity and avoid participating, thereby missing out on potential gains (participation puzzle) Badarinza et al. [2016].

A solution to the participation puzzle consists of financial advising. Relying on financial advising can provide potential investors with more information and clarify the trade-off they face when deciding whether to invest and how to diversify their portfolio. However, financial advising can be costly and may disproportionately penalize population groups who would benefit the most from proper financial planning[2].

Robo-advisors - the provision of financial advice through algorithms on digital platforms typically with little to no human intervention (D'Acunto et al. [2019])- offers a more recent solution to the puzzle. Its scalability, achieved by reducing costs, set the stage for enabling a significantly larger share of households to access financial guidance (D'Acunto and Rossi [2021]).

This study has two goals: (i) to analyze the diffusion of robo-advisors in an advanced economy like Italy, where the participation puzzle is significant, also delving into the characteristics of its users; and (ii) to explore whether the use of this tool influences willingness to engage in financial investments.

Ongoing discussions on robo-advisors highlight both opportunities and challenges. Behavioral tendencies often undermine individuals' investment decisions. For instance, difficulty focusing, limited information gathering, and excessive fear of losses can result in overly conservative choices, while overconfidence may drive unnecessary trading. Robo-advisors can help mitigate these effects by offering automated financial guidance, encouraging individuals to adopt behaviors aligned with those of rational agents. With regard to challenges, one lies in the limited transparency of algorithmic systems, which may prevent investors from fully understanding the processes behind the formulation of advice. Moreover, algorithms can be trained on datasets that reflect existing distortions, or they may fail to account for the most recent market developments.

[1]The authors thank Riccardo De Bonis, Daniela Marconi, Marco Marinucci, Noemi Oggero, and Mariacristina Rossi, as well as the participants of the International Workshop on Household Finance, Collegio Carlo Alberto - University of Turin, 2024, the 65th Annual Scientific Meeting of the Italian Economic Society, University of Urbino, 2024, and the workshop on Financial Education organized by Politecnico di Milano and Banca d'Italia, 2025 for fruitful discussions and comments. Any remaining errors are our own. The opinions expressed herein are solely those of the authors and do not necessarily reflect the views of their affiliated institution.

[2]Calvet et al. [2007], Campbell [2006], D'Acunto et al. [2019], Guiso et al. [2003], Linnainmaa et al. [2020], Mankiw and Zeldes [1991], Zinman [2015]

The analysis is based on a sample of nearly 5,000 individuals, aged between 18 and 79, representative of the population residing in Italy. Data are drawn from the 2023 IACOFI survey on financial literacy in Italy, conducted by the Bank of Italy[3]. The sampling methodology follows the framework developed by the International Network on Financial Education (INFE) of the OECD.

For identification purposes, we employ multivariate models that control for a broad set of individual characteristics. Crucially, we include multiplicative effects at the bank —based on the institution with which the respondent maintains their primary financial relationship—and the provincial level. This strategy accounts for (unobserved) individual factors influencing the choice of financial institution, as well as those related to the respondent's place of residence. To examine the relationship between robo-advisor usage and engagement in financial investments, we extend the model using an instrumental variable approach, complemented by a placebo test conducted to verify whether the data are consistent with the hypothesis underlying the identification strategy, on which the validity of the results relies.

The main findings are as follows. First, 15% of the people in Italy use robo-advisors. The adoption of robo-advisor services is more prevalent among men, individuals with higher income levels, and those with stronger digital skills. Interestingly, however, robo-advisors are also more commonly used by individuals with low levels of financial literacy, including key concepts such as the risk-return trade-off and the benefits of portfolio diversification. This finding is supported by evidence showing that robo-advisor users tend to report greater difficulties in managing their personal finances, including challenges in making ends meet. Second, the analysis shows that the use of robo-advisor services increases individuals' participation in financial markets, namely the propensity to invest in stocks, bonds, and investment funds.

The remainder of the paper is organized as follows. Section 2 presents a review of the literature, Section 3 illustrates the empirical analysis, and Section 4 offers the conclusion along with its policy implications.

2 Review of the literature

The spread of robo-advisors as a financial advising tool is relatively recent, and the academic literature on the topic is growing (see D'Acunto and Rossi [2023]).

Robo-advisors may help people manage their current financial needs, providing a comprehensive balance sheet view that reduce debt balances and improve loan repayment. Through the design of an RCT in which robo-advisors are offered to a set of UK consumers, Chak et al. [2022] find that free robo-advisors improve loan repayment choices.

[3] `https://www.bancaditalia.it/statistiche/tematiche/indagini-famiglie-imprese/alfabetizzazione/index.html?com.dotmarketing.htmlpage.language=1`

Lee [2019] documents how overspending alerts and automatic financial goals can reduce cumulative spending while Gargano and Rossi [2024] use a difference-in-differences strategy to show that automatic financial goals can increase savings rates.

With regard to financial investments, risk-adjusted returns of portfolios generated by robo-advisors can be higher in comparison to those obtained through static or rule-based approaches (Capponi et al. [2022]). An important aspect relates to costs. Jung et al. [2018] analyze robo-advisor portfolios versus traditional mutual funds to show that the former delivers comparable or better risk-adjusted returns, mainly due to lower fees and automated rebalancing; Reher and Sokolinski [2021] document how rob-advisors can improve the performance of financial investments, especially for modestly wealthy households (Reher and Sokolinski [2021]); according to Uhl and Rohner [2018], robo-advisors are an efficient alternative to traditional advice, particularly for investors seeking low-cost solutions. Other aspects relate to the mitigation of prominent behavioral biases — including the disposition effect, trend chasing, and the rank effect — which contribute to better diversification in the portfolios suggested by robo-advisors (D'Acunto et al. [2019]) and to improved investor attention (Bianchi and Brière [2021]). Finally, robo-advisors can enhance traditional advice by addressing issues—such as recommendation ambiguity—that have at times been associated with human interactions (Philippon [2016]).

With regard to challenges, robo-advisors may produce biased outcomes when trained on data that reflect past distortions or do not incorporate recent market developments. Algorithms can lack transparency—often functioning as "black boxes"—with limited clarity on how decisions are made (Binns et al. [2018]). Scherer and Lehner [2025] use web-scraped portfolio recommendations to show that robo-advisors tend to prioritize simplicity and client perceptions over generating outcomes aligned with normative (Merton-type) models. Along the same lines, (Belanche et al. [2019], Tan [2020]) show that algorithms may fail to capture users' specific situations or may oversimplify the advice, potentially resulting in recommendations only partially tailored to individual needs. Furthermore, as with traditional advising, there may be cases in which firm–client interest misalignments may lead robo-advisors to offer suboptimal recommendations (Foerster et al. [2017]).

Despite the growing body of literature, a comprehensive analysis of the characteristics of robo-advisor users has not yet been conducted. This study aims to fill this gap through a detailed examination of robo-advisor users in Italy, identifying their personal characteristics, with emphasis on financial literacy and resilience to shocks. It will also investigate whether robo-advisors are used as a complement to traditional forms of advising and, finally, whether it is able to support participation in financial markets. The importance of conducting this study in Italy lies in the country's low participation in financial markets, limited financial literacy compared to international standards, and the rapid digitalization of financial services. Italy thus offers a unique context to assess whether robo-advisors can promote a responsible and informed financial inclusion.

3 Empirical analysis

We investigate the prevalence of robo-advisors and the characteristics of their users, as well as whether robo-advisor usage influences individuals' propensity to participate in financial markets in Italy.

The empirical analysis uses bivariate statistics and a multivariate model (linear probability model) that controls for a broad set of sociodemographic characteristics. We employ specifications that include a rich set of fixed effects to account for unobserved heterogeneity at both the provincial and bank levels: severe specifications include multiplicative bank and province effects, which allow us to observe how robo-advisor usage varies among individuals from the same province and clients of the same bank. To enforce causality, the analysis of the effects of robo-advisors on participation in financial markets employs an instrumental variables approach.

3.1 Data and descriptive statistics

We use a novel dataset from the IACOFI survey on financial literacy, conducted by the Bank of Italy in 2023. The dataset covers adults aged 18 to 79 residing in Italy at the time of the interview, with a sample of 4,862 individuals, which is representative of the target population. The sample design considers 'quotas' based on geographical location and municipality size and the statistical units are post-stratified by gender, age, and education level. Interviews were conducted via telephone using the CATI (Computer-Assisted Telephone Interviewing) method.

The survey provides information on several individuals socio-demographic attributes, financial and digital literacy and investment choices; data on the respondent's primary bank is also collected[4].

We identify robo-advisor users as individuals who responded *often* or *very often* to the statement: 'In the last 12 months, I consulted an online platform to receive financial advice (robo-advice)'.

Table 1 reports some descriptive statistics. In Italy, approximately 15% of individuals reported using robo-advisors for financial advice in the 12 months prior to the interview. The use of robo-advisors is more common among individuals with higher educational attainment, higher income, and aged between 35 and 64 (Figure 1 and Table 2).

3.2 Robo-advisors and financial knowledge

We study the relationship between robo-advisor usage and individuals' financial knowledge—measured by their ability to correctly answer all the Big Three financial literacy

[4]Information about respondents' primary bank is included in the Italian survey questionnaire but is not originally part of the OECD/INFE questionnaire. This information is provided by 73 percent of respondents.

questions, i.e., questions on interest rates, inflation, and risk diversification (Lusardi and Mitchell [2014]). Additional dimensions of financial knowledge are also explored, such as the understanding of the risk–return relationship, as well as the tendency to respond "I don't know", which is important for identifying the level of confidence in one's own knowledge.

The empirical analysis shows that users of robo-advisors exhibit lower levels of financial knowledge. Among those who correctly answered all three Big Three questions, 11.7% used a robo-advisor, while this percentage increases to 15.6% among those who answered at least one question incorrectly. Moreover, the data show that robo-advisor users are not only less financially knowledgeable, but also more confident in their financial abilities (19.5%) compared to their peers (10.5%, Figure 2)[5].

Turning to multivariate analysis (Table 2), the results confirm the negative link between the use of robo-advisors and financial knowledge, even in specifications that include bank effects. The coefficient associated with the frequency of the "I do not know" responses — that may reflect a lack of confidence in one's financial knowledge (Bucher-Koenen et al. [2024])[6]—is also negative; in other words, the higher the level of self-confidence, the greater the likelihood of using a robo-advisor.

We broaden the analysis by exploring the relationship between robo-advisor usage and each of the individual concepts included in the Big Three financial literacy score, as well as other dimensions of financial knowledge, such as those examined in OECD/INFE financial literacy surveys (Table 3). Notably, the results indicate that robo-advisor users show lower proficiency in understanding key financial concepts—such as the risk-return tradeoff and risk diversification—despite the importance of these principles for making informed investment decisions.

3.3 Robo-advisors and financial resilience

The analysis of robo-advisor users' profiles continues by examining their ability to cope with financial difficulties. We use the variables included in the financial resilience indicator considered by OECD/INFE [2022]: (i) ability to cover a monthly income expense without borrowing; (ii) whether income is sufficient to meet living expenses; (iii) capacity to sustain living expenses for at least three months without borrowing in the absence of income; and (iv) whether they have money left at the end of the month. We examine both a composite indicator that aggregates the four dimensions and each component

[5] Consistent with this evidence, the data also indicate that robo-advisors are more frequently used by 'overconfident' individuals than by their peers. Individuals are classified as 'overconfident' if they rate their financial knowledge as equal to or above average, yet fail to correctly answer at least two of the Big Three questions.

[6] Since the Big Three score does not capture the lack-of-confidence component, explicitly including the frequency of 'I do not know' responses in multivariate regressions can help partially control for this dimension.

individually.

Robo-advisors are more frequently used by individuals who report lower resilience to shocks: robo-advisor users show an aggregate financial resilience score of 2.2 out of a maximum of 4, compared to 2.7 among non-users[7]. Similar results are obtained when looking at the individual questions: usage of robo-advisors is 25% among those who are unable to cover expenses without borrowing, compared to 15% among their peers; usage is higher among those whose income does not cover living expenses (18% versus 15%), those who could not sustain expenses for three months without borrowing in the absence of income (19% versus 15%), and those who do not have money left at the end of the month (16% versus 14%, Figure 6).

These results, which are qualitatively consistent with the findings from the multivariate analysis (Figure 6), suggest that robo-advisor users are less capable of effectively coping with unexpected financial shocks. They also complement evidence indicating that these individuals tend to have relatively lower levels of financial knowledge.

3.4 Robo-advice, bank advice, and independent advice

It may be interesting to investigate whether the use of robo-advisors complements other sources of advice, such as traditional advising services provided by bank-affiliated consultants or independent professionals. To the best of our knowledge, so far no studies have explored these associations.

This analysis is subject to a caveat: data on traditional financial advice are available only for individuals who have purchased financial products in the past two years. Consequently, the investigation can only be conducted within this specific subsample[8].

According to the descriptive statistics, approximately 45% of the sample did not seek any form of financial advice. Conversely, around 55% relied on some type of advisory service—either through robo-advisors or traditional sources such as bank-affiliated or independent financial advisors (see 3). Specifically, 39% (=25+8+3+3) consulted a bank advisor, 21% an independent advisor, and 16% used a robo-advisor.

Individuals who adopt robo-advisors are more likely to seek advice from independent advisors rather than from bank-affiliated advisors (Figure 4): the percentage of robo-advisor users is higher among individuals who consult an independent advisor (30%) than among those who seek advice from a bank officer (12%).

The issue is further explored in a multivariate setting (Table 4). The econometric analysis shows that the use of robo-advisors positively correlates with independent advice, consistent with a pattern of complementarity. This indicates that digitally oriented individuals tend to integrate the automated channel with forms of independent profes-

[7]The aggregate financial resilience score is the sum of the four aforementioned (dummy) indicators.

[8]By contrast, all participants were asked questions concerning their use of robo-advisors.

sional advice; there is also a negative association between traditional banking advice and robo-advice, suggesting a substitutive relationship between these two sources of guidance.

3.5 Robo-advisors and satisfaction with banking services

We analyze whether robo-advisor users are satisfied with the advising services provided by their primary bank. We consider several dimensions, such as the suitability of the products recommended by bank officers, the clarity of explanations regarding financial services, the waiting time to speak with officers, and the quality of the digital services.

We define respondents as 'dissatisfied' if they declare to disagree or totally disagree to the statements of satisfaction with respect to the previous dimensions. The results show that the frequency of dissatisfaction with the quality of banking services is higher among those who use robo-advisors (over 20%) compared to their peers (less than 10%, Figure 5), across all dimensions. Thus, adopters of robo-advisors exhibit higher overall dissatisfaction. The positive relationship between dissatisfaction with banking services and the use of robo-advisors remains robust in a multivariate context (Table 5).

3.6 Robo-advisors and financial market participation

This paragraph analyzes the relationship between the use of robo-advisors and participation in financial markets. Financial market participation is defined as having invested in at least one of the following classes of financial instruments within the 12 months prior to the interview: stocks, bonds, or other investment products (such as mutual funds or open-ended funds).

We use an OLS linear probability model that controls for several variables, including gender, age, income, education, occupational status, risk aversion and financial knowledge. The latter is measured by a dummy that equals one if individuals correctly answer all the Big Three questions, and zero otherwise. We include macro-area and, in separate regressions, province- and bank- effects to control for unobserved components that could correlate with financial market participation.

The results are presented in Table 7. The usage of robo-advisors positively associates with financial market participation. The coefficient indicates that the probability of participation increases by about 17 percentage points among robo-advisor users. This finding aligns qualitatively with D'Acunto et al. [2019], who examined the link between usage of robo-advisors and retail investors' trading behavior. With regard to control variables, consistent with Lusardi [2009], Lusardi and Mitchell [2009], Van Rooij et al. [2011], participation is also higher among financially knowledgable individuals and, in line with Guiso et al. [2008], among risk-tolerant individuals.

3.6.1 Instrumental variable: digital skills

The OLS estimates might be exposed to endogeneity. Endogeneity might arise because the prospect of financial market participation may increase ex-ante the likelihood of using robo-advisor applications (reverse causality). Additionally, unobserved factors correlated with both robo-advisor usage and financial market participation could generate spurious correlations (omitted variable bias). We adopt an instrumental variable approach (IV) to mitigate these issues and to isolate (less endogenous) variation in robo-advisor usage.

A valid instrument must satisfy two conditions: i) relevance—the instrument (z) should be correlated with robo-advisor usage; and ii) exclusion restriction—the instrument (z) should influence participation through robo-advisor usage. Our instrument is the individuals' level of digital skills, which are plausibly unrelated to financial management activities. Notably, the list of digital skills excludes any aspects related to financial management and includes only those strictly pertaining to digital competencies.

The list of digital skills includes: using e-mails, writing documents on laptop, using instant messaging apps, making calls over the internet, and participating in social networks. The instrument ranges from zero to five, reflecting the total number of digital skills the individual possesses[9].

To validate our exclusion restriction assumption, we conduct a placebo test.

The results of the IV regression are presented in Table 8. In the first stage regression (column 2), we observe a positive correlation between digital skills and robo-advisor usage, which is in line with the relevance condition. This is plausible, as robo-advisor users are likely to be familiar with digital tools for general purposes.

In the second-stage regression (column 1), the IV estimate of the effect of robo-advisors on financial market participation is positive, statistically significant and larger than the OLS estimate.

We verify whether the data are consistent with our working assumption about the exclusion restriction. Specifically, our placebo test removes the channel linking digital skills and participation by considering the subsample of individuals who do not use robo-advisors (3,598 observations). If the working hypothesis holds, the link between digital skills and participation should disappear among these individuals. Our results support our working assumption (column 3) as the coefficient of digital skills is statistically null when estimated among individuals who do not use robo-advisors.

[9]Each skill is scored as 1 if the individual reported engaging in that activity ('often' or 'very often') during the year prior to the interview.

4 Concluding remarks

Robo-advisors have been adopted by approximately 15% of the adult population in Italy. Robo-advisors are more commonly adopted by men, individuals with higher incomes, and those with strong digital skills. Interestingly, their usage is also more prevalent among people with lower levels of financial literacy and those who report difficulties in managing unexpected financial shocks. Furthermore, our findings suggest that robo-advisors can play a role in increasing participation in financial markets.

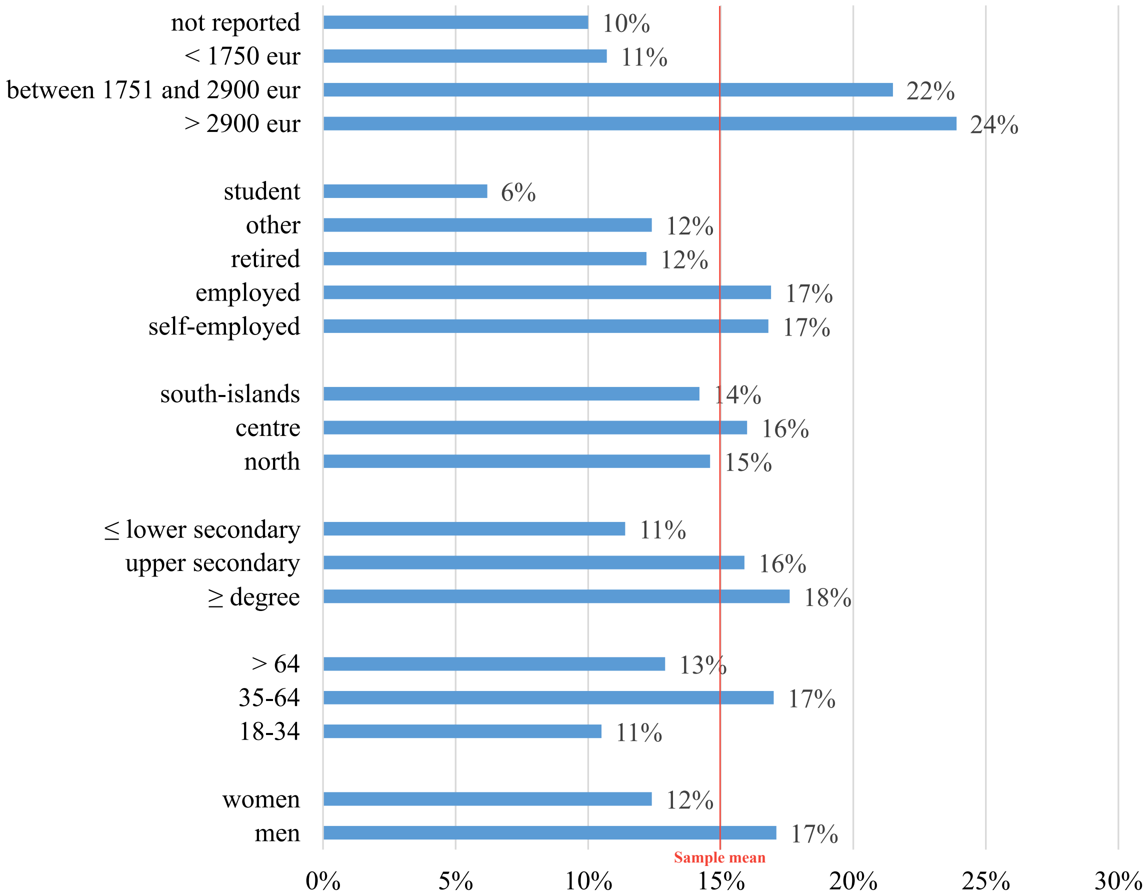
These findings suggest that robo-advisors may support individuals with limited financial knowledge in managing their finances more effectively by encouraging disciplined behavior and fostering decisions that align more closely with those of a rational agent. Nonetheless, concerns remain about the potential risks of uncritically delegating financial decisions to algorithms—particularly among those with low financial literacy. These risks cannot be quantified in our paper, as we lack evidence regarding the outcomes of financial investments made through the use of robo-advisors.

From a policy perspective, the findings underscore the need to improve financial education, covering both the benefits and limitations of robo-advisors and general financial literacy. Strengthening users' financial knowledge can enable more informed decision-making, ensuring that individuals engage with robo-advisors in a way that maximizes potential while mitigating risks.

Appendix

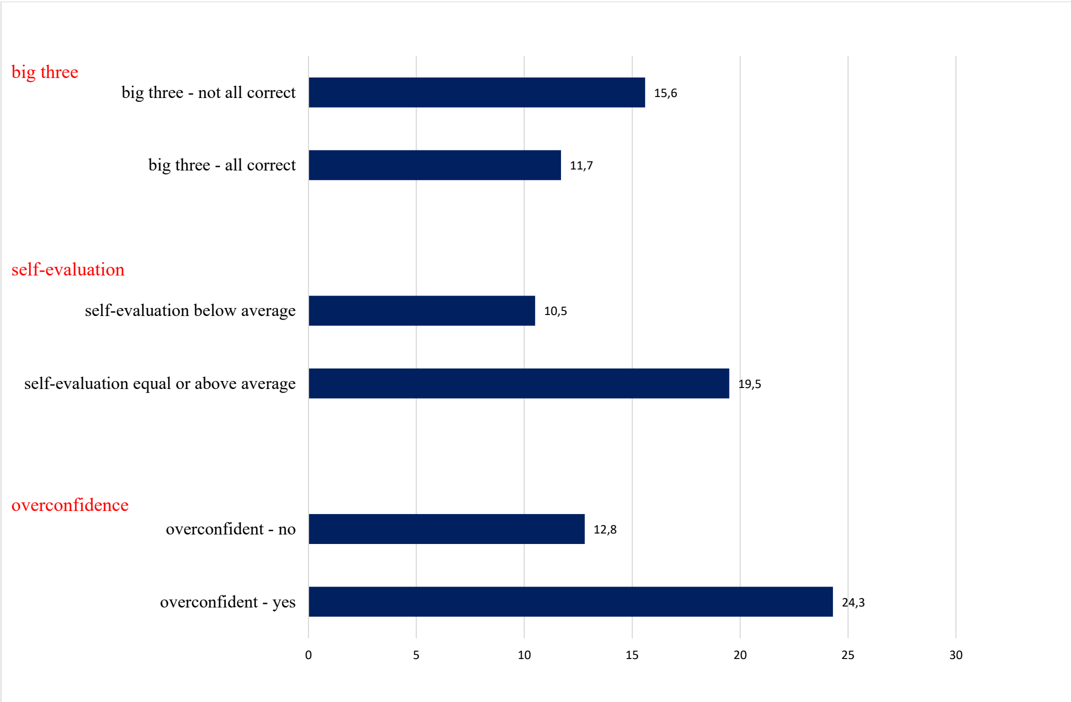
A. Figures

Figure 1: Robo-advisors and user profiles: bivariate analysis
(percentages)



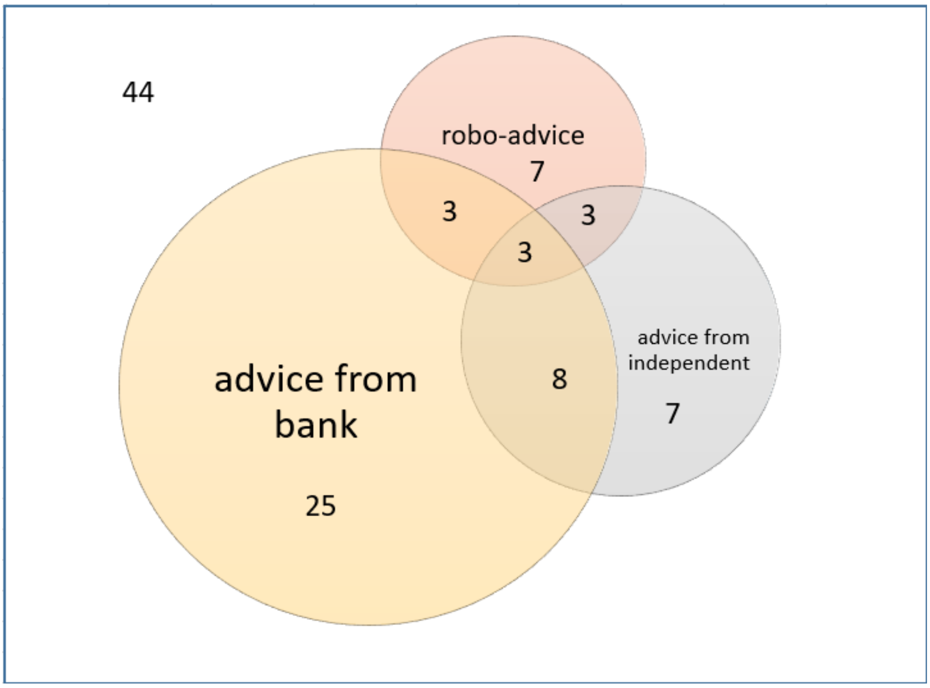
Source: Iacofi 2023, Bank of Italy. On the x-axis, the percentage of robo-advisor users.

Figure 2: Robo-advisors and financial knowledge: bivariate analysis
(percentages)



Source: Iacofi 2023, Bank of Italy. On the x-axis, the percentage of robo-advisor users.

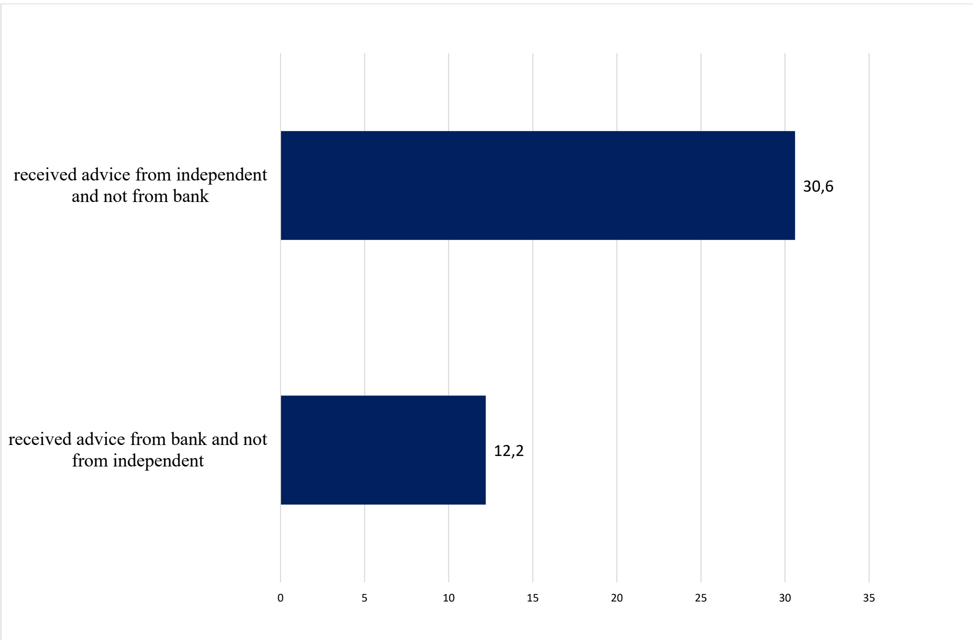
Figure 3: Robo-advice, bank advice and independent advice
(percentages)



Source: Iacofi 2023, Bank of Italy. The figure is based on data for individuals who have purchased (any) financial products in the last 24 months (the only group for whom data on traditional advice are available). The diagram shows the use of each form of financial advice either in combination or in isolation - the percentages of intersections and non-intersections - with other forms of advice: robo-advice, bank advice, and advice from an independent professional. For example: 25% is the percentage of those who receive advice from the bank, but neither from robo-advisors nor from an independent professional; 39% (= 25% + 8% + 3% + 3%) is the overall percentage of individuals who receive advice from the bank; 44% does not receive any type of financial advice.

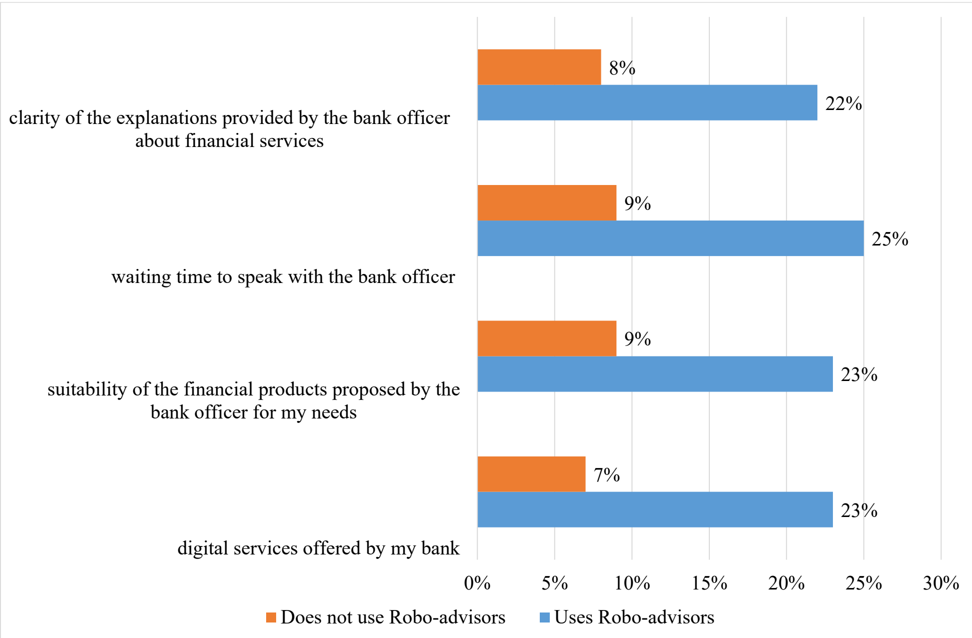
Figure 4: Robo-advisor adoption among users of traditional financial advisory services

(percentages)



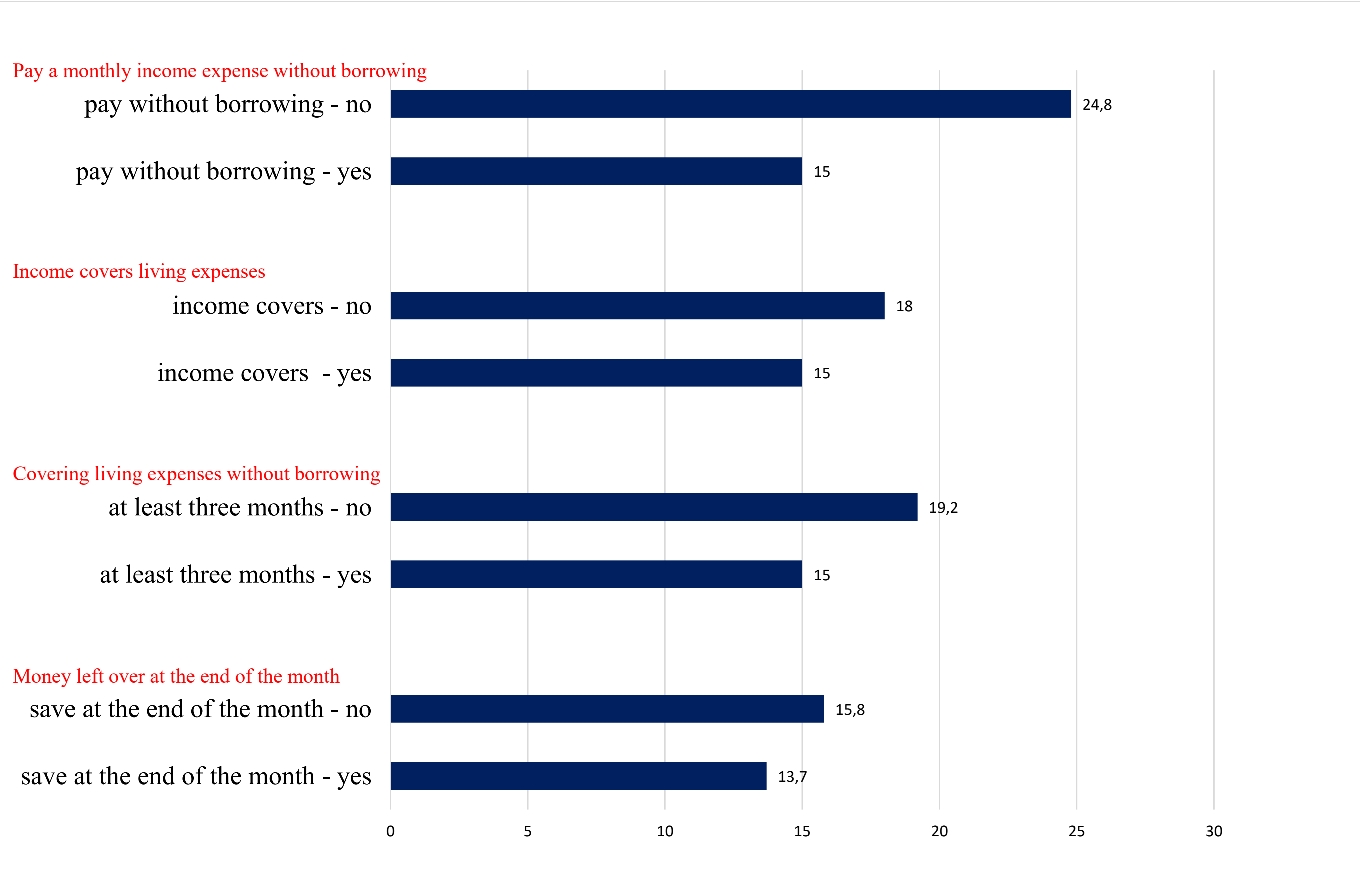
Source: Iacofi 2023, Bank of Italy. On the x-axis, the percentage of robo-advisor users.

Figure 5: Robo-advisors and satisfaction with banking services: bivariate analysis
Individuals dissatisfied with *(percentages)*



Source: Iacofi 2023, Bank of Italy. On the x- axis, the percentage of individuals dissatisfied with each of the banking services listed.

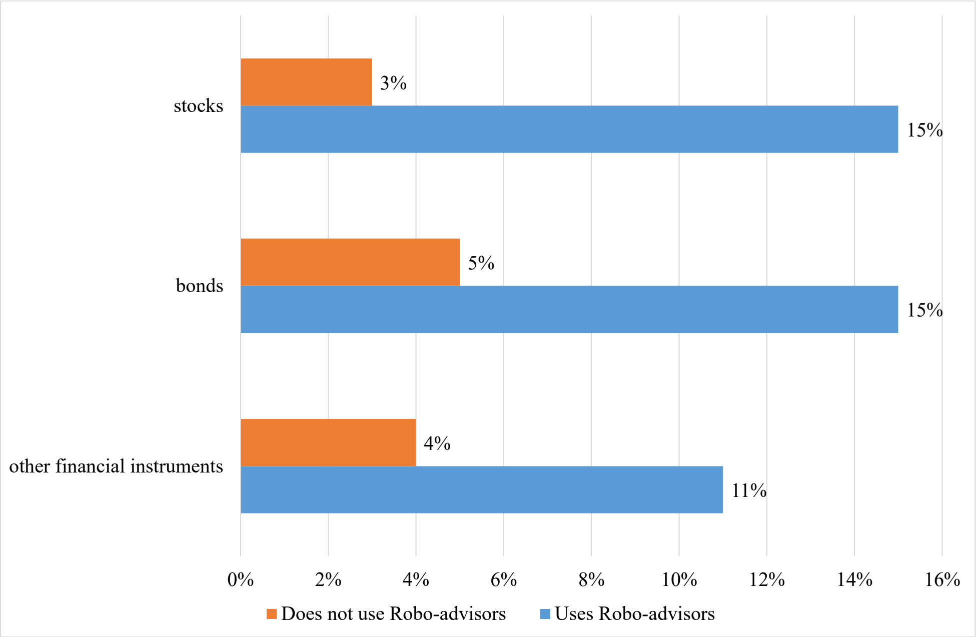
Figure 6: Robo-advisors and financial resilience: bivariate analysis *(percentages)*



Source: Iacofi 2023, Bank of Italy. On the x-axis, the percentage of robo-advisor users.

Figure 7: Robo-advisors and participation in financial markets: bivariate analysis

(percentages)



Source: Iacofi 2023, Bank of Italy.On the x-axis, the percentage of individuals who have purchased the financial product in the 12 months prior to the interview.

B. Tables

Table 1: Descriptive statistics

	Mean	St.Dev.	Min	Max	n
women	0.51	0.50	0	1	4,862
18-34 year old	0.22	0.41	0	1	4,862
35-64 year old	0.56	0.49	0	1	4,862
$>$ 64 year old	0.21	0.40	0	1	4,862
$\leq$ lower secondary	0.38	0.48	0	1	4,862
upper secondary	0.42	0.49	0	1	4,862
$\geq$ degree	0.18	0.38	0	1	4,862
employed	0.48	0.50	0	1	4,862
self-employed	0.08	0.28	0	1	4,862
retired	0.21	0.41	0	1	4,862
student	0.07	0.26	0	1	4,862
other	0.14	0.35	0	1	4,862
$<$ 1750 euro	0.31	0.46	0	1	4,862
1750-2900 euro	0.28	0.45	0	1	4,862
$>$ 2900 euro	0.07	0.25	0	1	4,862
income not reported	0.32	0.47	0	1	4,862
big three	0.20	0.39	0	1	4,862
high self-evaluation	0.49	0.50	0	1	4,453
over-confidence	0.18	0.39	0	1	4,453
robo-advisor use	0.15	0.35	0	1	4,427
financial market participation	0.12	0.32	0	1	4,660
narrow trust	2.40	0.94	0	4	4,381
digital skills	2.99	1.89	0	5	4,862
dissatisfied with products offered by bank officers	0.11	0.32	0	1	4,862
dissatisfied with clarity of explanations of bank officers	0.11	0.31	0	1	4,862
dissatisfied with waiting time to speak with bank officers	0.11	0.31	0	1	4,862
dissatisfied with bank's digital services	0.10	0.30	0	1	4,862
pay a monthy income expense without borrowing	0.75	0.43	0	1	3,526
income covers living expenses	0.86	0.35	0	1	4,265
covering living expenses without borrowing for at least three months	0.45	0.50	0	1	3,423
money left over at the end of the month	0.31	0.46	0	1	4,459

Source: Iacofi 2023, Bank of Italy.
Note: All figures are weighted.

Table 2: Robo-advisors and user profiles: multivariate analysis

	(1)	(2)	(3)	(4)	(5)
women	-0.044***	-0.044***	-0.041***	-0.043***	-0.048***
18-34 year old	-0.041**	-0.042**	-0.041**	-0.019	-0.038*
> 64 year old	0.014	0.015	0.012	0.065***	0.029
≤ lower secondary	-0.017	-0.017	-0.017	-0.021	-0.022
≥ degree	0.007	0.006	0.006	0.049***	0.051**
self-employed	-0.013	-0.013	-0.018	-0.010	-0.016
retired	-0.051**	-0.052**	-0.047*	-0.086***	-0.078***
student	-0.029	-0.028	-0.041*	-0.084***	-0.124***
other	0.014	0.013	0.005	0.010	-0.002
< 1750 euro	-0.091***	-0.091***	-0.089***	-0.012	-0.001
> 2900 euro	0.035	0.035	0.038	0.084***	0.072**
risk tolerant	0.021**	0.021**	0.018*	-0.007	-0.006
south-islands	-0.007				
north	-0.009				
Big Three	-0.099***	-0.099***	-0.092***	-0.087***	-0.075***
% don't know in Big Three	-0.108***	-0.108***	-0.109***	-0.092***	-0.065**
adj-R^2	0.049	0.049	0.064	0.096	0.112
Fixed effects	-	macro-area	province	bank	bank × province
N	4,427	4,427	4,427	3,154	2,527

Source: Iacofi 2023, Bank of Italy.
Note: The dependent variable is a dummy equal to 1 if the respondent states s/he consulted a robo-advisor to receive financial advice within the 12 months prior to interview. Covariates include a dummy variable taking value one for those who did not answer the question assessing risk tolerance, and a dummy variable taking value one for those who did not declare their income. Estimates use sample weights. Standard errors are clustered by municipality of respondent's residence. Omitted categories are: men; 35-64 years old; upper secondary diploma; employed; monthly income of 1750-2900 euro; residence in the central regions of Italy; and who wrongly answers to at least one of the big three questions. Risk tolerant varies between 0 (risk averse) and 3 (risk lover); percentage of don't know answers in the big three can take values 0, 1/3, 2/3, 1. Statistical significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Robo-advisors and financial knowledge (concepts): multivariate analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
women	-0.048***	-0.051***	-0.049***	-0.050***	-0.048***	-0.049***	-0.047***
18-34 year old	-0.041**	-0.035*	-0.039*	-0.041**	-0.037*	-0.035*	-0.036*
$>$ 64 year old	0.028	0.017	0.026	0.027	0.019	0.021	0.032
$\leq$ lower secondary	-0.024	-0.026	-0.024	-0.025	-0.022	-0.027	-0.019
$\geq$ degree	0.048**	0.052**	0.049**	0.051**	0.051**	0.056***	0.051**
self-employed	-0.017	-0.006	-0.015	-0.015	-0.006	-0.002	-0.015
retired	-0.080***	-0.067**	-0.079***	-0.079***	-0.065**	-0.061**	-0.078***
student	-0.124***	-0.129***	-0.125***	-0.123***	-0.138***	-0.130***	-0.123***
other	-0.002	-0.002	-0.002	-0.002	0.004	-0.005	-0.004
$<$ 1750 euro	-0.004	-0.009	-0.006	-0.007	-0.003	-0.007	-0.002
$>$ 2900 euro	0.066**	0.055*	0.064*	0.067**	0.068**	0.065**	0.068**
risk tolerant	-0.006	-0.005	-0.007	-0.006	-0.005	-0.009	-0.008
FK1: inflation	-0.024						
FK1: don't know	-0.017						
FK2: interest on loan		-0.169**					
FK2: don't know		-0.057					
FK3: simple interest			-0.016				
FK3: don't know			-0.001				
FK4: compound interest				-0.028			
FK4: don't know				0.010			
FK5: risk-return relationship					-0.088***		
FK5: don't know					-0.023		
FK6: inflation and living cost						-0.176***	
FK6: don't know						-0.057	
FK7: risk diversification							-0.058***
FK7: don't know							-0.067***
adj-R^2	0.105	0.122	0.105	0.106	0.119	0.143	0.112
bank$\times$province fixed effects	yes	yes	yes	yes	yes	yes	yes
N	2,527	2,527	2,527	2,527	2,527	2,527	2,527

Source: Iacofi 2023, Bank of Italy.
Note: The dependent variable is a dummy variable equal to 1 if the respondent states s/he consulted a robo-advisor to receive financial advice within the 12 months prior to interview. Covariates include a dummy variable taking value one for those who did not answer the question assessing risk tolerance, and a dummy variable taking value one for those who did not declare their income. Estimates use sample weights. Standard errors are clustered by municipality of respondent's residence. Omitted categories are: men; 35-64 years old; upper secondary diploma; employed; monthly income of 1750-2900 euro. Statistical significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4: Robo-advice, bank advice, and independent advice: multivariate analysis

	(1)	(2)	(3)	(4)	(5)
women	-0.030	-0.030	-0.029	-0.038	-0.063**
18-34 year old	-0.059*	-0.059*	-0.053	-0.036	-0.103**
> 64 year old	0.078*	0.078*	0.058	0.063	0.028
≤ lower secondary	0.010	0.009	0.009	0.016	0.048
≥ degree	0.012	0.013	0.020	0.052*	0.027
self-employed	-0.034	-0.034	-0.046	-0.054	-0.101**
retired	-0.172***	-0.170***	-0.144***	-0.121***	-0.124**
student	-0.134***	-0.133***	-0.152***	-0.104***	-0.175**
other	-0.008	-0.007	-0.001	-0.005	0.065
< 1750 euro	-0.109***	-0.108***	-0.096***	-0.059*	-0.038
> 2900 euro	0.014	0.013	0.001	0.041	0.060
risk torelant	0.022	0.022	0.019	0.024	0.028
south-islands	0.018				
north	-0.018				
Big three	-0.104***	-0.104***	-0.108***	-0.113***	-0.078*
% don't know in Big three	-0.086**	-0.086**	-0.099**	-0.078*	-0.014
Received advice from the bank	-0.067***	-0.067***	-0.064***	-0.022	-0.010
Received advice from independent	0.123***	0.121***	0.127***	0.090***	0.114**
adj-R^2	0.096	0.095	0.107	0.145	0.217
Fixed effects	-	macro-area	province	bank	bank × province
N	1,264	1,264	1,260	984	610

Source: Iacofi 2023, Bank of Italy.

Note: Sample of people who purchased any financial product in the last 24 months. The dependent variable is a dummy variable equal to 1 if the respondent states s/he consulted a robo-advisor to receive financial advice within the 12 months prior to interview. Covariates include a dummy variable taking value one for those who did not answer the question assessing risk tolerance, and a dummy variable taking value one for those who did not declare their income. Estimates use sample weights. Standard errors are clustered by municipality of respondent's residence. Results hold including bank×macroarea fixed effects. Omitted categories are: men; 35-64 years old; upper secondary diploma; employed; monthly income of 1750-2900 euro; residence in the central regions of Italy; who wrongly answers to at least one of the big three questions; who did not received advice from the bank; and who did not receive advice from an independent professional advisor; percentage of don't know answers in the big three can take values 0, 1/3, 2/3, 1. Risk tolerant varies between 0 (risk averse) and 3 (risk lover). Statistical significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Robo-advisors and satisfaction with banking services: multivariate analysis

	(1)	(2)	(3)	(4)
women	-0.047***	-0.044***	-0.045***	-0.041***
18-34 year old	-0.032	-0.033	-0.030	-0.030
$>$ 64 year old	0.021	0.019	0.015	0.016
$\leq$ lower secondary	-0.033*	-0.026	-0.031	-0.025
$\geq$ degree	0.047**	0.052**	0.051**	0.044**
self-employed	-0.014	-0.012	-0.008	-0.014
retired	-0.072***	-0.070***	-0.061**	-0.070***
student	-0.126***	-0.120***	-0.130***	-0.130***
other	-0.007	-0.011	-0.013	-0.017
$<$ 1750 euro	0.005	0.000	0.004	0.002
$>$ 2900 euro	0.067**	0.064*	0.064*	0.065**
risk tolerant	-0.001	-0.001	-0.001	0.001
Big three	-0.054***	-0.060***	-0.063***	-0.062***
dissatisfaction (digital services offered by the bank)	0.160***			
dissatisfaction (clarity of explanations of bank officers)		0.128***		
dissatisfaction (suitability of products offered by the bank)			0.167***	
dissatisfaction (waiting time to speak with bank officers)				0.195***
adj-R^2	0.129	0.123	0.133	0.141
bank$\times$province fixed effects	yes	yes	yes	yes
N	2,527	2,527	2,527	2,527

Source: Iacofi 2023, Bank of Italy.

Note: The dependent variable is a dummy variable equal to 1 if the respondent states s/he consulted a robo-advisor to receive financial advice within the 12 months prior to interview. Covariates include a dummy variable taking value one for those who did not answer the question assessing risk tolerance, and a dummy variable taking value one for those who did not declare their income. Estimates use sample weights. Standard errors are clustered by municipality of respondent's residence. Omitted categories are: men; 35-64 years old; upper secondary diploma; employed; monthly income of 1750-2900 euro; who wrongly answers to at least one of the big three questions; and who is satisfied with the relationship with their bank according to four aspects: digital services offered by the bank, clarity of explanations of bank officers, suitability of products offered by the bank, and waiting time to speak with the bank officers. Risk tolerant varies between 0 (risk averse) and 3 (risk lover). Statistical significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6: Robo-advisors and financial resilience: multivariate analysis

	(1)	(2)	(3)	(4)
women	-0.056***	-0.043**	-0.049***	-0.061***
18-34 year old	-0.020	-0.027	-0.032	-0.042**
$>$ 64 year old	0.035	0.029	0.056	0.040
$\leq$ lower secondary	-0.027	-0.018	-0.037	-0.040**
$\geq$ degree	0.054**	0.047**	0.068**	0.062***
self-employed	-0.028	-0.028	-0.003	-0.006
retired	-0.092***	-0.083***	-0.075*	-0.090***
student	-0.243***	-0.131***	-0.159**	-0.108***
other	-0.023	-0.023	0.004	-0.019
$<$ 1750 euro	-0.028	-0.012	-0.009	0.001
$>$ 2900 euro	0.071*	0.077**	0.068*	0.075**
risk tolerant	0.016	0.005	0.001	-0.008
big three	-0.076***	-0.059***	-0.061***	-0.054***
Pay a monthly income expense without borrowing	-0.112***			
Income covers living expenses		-0.101***		
Covering living expenses without borrowing for at least three months			-0.048**	
Money left over at the end of the month				-0.057***
adj-R^2	0.116	0.120	0.098	0.129
bank$\times$province fixed effects	yes	yes	yes	yes
N	1,807	2,231	1,760	2,390

Source: Iacofi 2023, Bank of Italy.
Note: The dependent variable is a dummy variable equal to 1 if the respondent states s/he consulted a robo-advisor to receive financial advice within the 12 months prior to interview. Covariates include a dummy variable taking value one for those who did not answer the question assessing risk tolerance, and a dummy variable taking value one for those who did not declare their income. Estimates use sample weights. Standard errors are clustered by municipality of respondent's residence. Omitted categories are: men; 35-64 years old; upper secondary diploma; employed; monthly income of 1750-2900 euro; who wrongly answers to at least one of the big three questions; and who is not able to cope with financial shocks according to four dimensions listed in the table (dummy variables). Risk tolerant varies between 0 (risk averse) and 3 (risk lover). Results hold when we use an aggregate measure of financial resilience as explanatory variable given by the sum of the four dimensions (dummy variables). Also, results hold when controlling for the number of family members in the household. Statistical significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Robo-advisors and participation in financial markets: multivariate analysis (OLS)

	(1)	(2)	(3)	(4)	(5)
women	-0.018	-0.018	-0.018	-0.005	0.004
18-34 year old	-0.095***	-0.096***	-0.095***	-0.065***	-0.064***
$>$ 64 year old	-0.066**	-0.065**	-0.063**	-0.083**	-0.112**
$\leq$ lower secondary	0.004	0.004	0.001	-0.014	-0.019
$\geq$ degree	-0.002	-0.002	-0.003	0.006	0.008
self-employed	0.057***	0.056***	0.059***	0.065***	0.063**
retired	0.063**	0.062**	0.058*	0.098***	0.108**
student	0.021	0.022	0.013	-0.028	-0.026
other	0.031*	0.030*	0.026	0.041*	0.038
$<$ 1750 euro	-0.088***	-0.088***	-0.087***	-0.068***	-0.072***
$>$ 2900 euro	0.045	0.046*	0.049*	0.061**	0.096***
risk tolerant	0.049***	0.049***	0.046***	0.033***	0.030***
south-islands	0.004				
north	0.022				
big three	0.107***	0.107***	0.109***	0.086***	0.071***
robo-advisor user	0.173***	0.173***	0.176***	0.136***	0.184***
adj-R^2	0.119	0.119	0.130	0.138	0.189
Fixed effects	-	macro-area	province	bank	bank $\times$ province
N	4,251	4,251	4,251	3,025	2,412

Source: Iacofi 2023, Bank of Italy.

Note: The dependent variable is a dummy variable equal to 1 if the respondent states s/he participated in the financial markets within the 12 months prior to interview. Covariates include a dummy variable taking value one for those who did not answer the question assessing risk tolerance, and a dummy variable taking value one for those who did not declare their income. Estimates use sample weights. Standard errors are clustered by municipality of respondent's residence. Omitted categories are: men; 35-64 years old; upper secondary diploma; employed; monthly income: 1750-2900 euro; residence in the central regions of Italy; who answers incorrectly to at least one of the Big Three questions; non-user of robo-advisors. Risk tolerant varies between 0 (risk averse) and 3 (risk lover). Statistical significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 8: Robo-advisors and participation in financial markets: multivariate analysis (IV)

	(1) IV	(2) First stage	(3) Placebo	(1) IV	(2) First stage	(3) Placebo
robo-advisor user	0.256**			0.478**		
women	-0.014	-0.048***	-0.022*	0.020	-0.052***	-0.010
18-34 year old	-0.093***	-0.047***	-0.085***	-0.056***	-0.037*	-0.060***
> 64 year old	-0.066**	0.033	-0.056*	-0.121**	0.046	-0.114**
≤ lower secondary	0.006	-0.012	-0.005	-0.009	-0.021	-0.021
≥ degree	-0.002	0.000	-0.010	-0.009	0.049**	-0.005
self-employed	0.056***	-0.009	0.059***	0.062**	0.000	0.038
retired	0.065**	-0.006	0.060*	0.127**	-0.048*	0.106**
student	0.024	-0.058**	0.002	0.010	-0.136***	-0.038
other	0.028	0.037*	0.033**	0.033	0.022	0.051*
< 1750 euro	-0.080***	-0.087***	-0.075***	-0.071***	-0.008	-0.060**
> 2900 euro	0.043	0.015	0.051*	0.079**	0.050	0.125***
risk tolerant	0.046	0.022**	0.042***	0.030***	-0.004	0.029**
big three	0.113***	-0.084***	0.109***	0.088***	-0.068***	0.076***
digital skills		0.036***	0.001		0.023***	0.005
N	4,251	4,251	3,598	2,412	2,412	2,090
F-stat		74.09			15.60	
Fixed effects	province	province	province	bank × province	bank × province	bank × province

Source: Iacofi 2023, Bank of Italy.

Note: dependent variables are a dummy equal to 1 if the respondent participated in the financial markets (columns (1) and (3)) and a dummy variable equal to 1 if the respondent states s/he consulted a robo-advisor to receive financial advice within the 12 months prior to interview (columns (2)). The instrumental variable is the individuals' level of digital skills. The list of digital skills includes: using e-mails, writing documents on laptop, using instant messaging apps, making calls over the internet, and participating in social net-works. The instrument ranges from zero to five. Each skill is scored as 1 if the individual reported engaging in that activity ('often' or 'very often') during the year prior to the interview. Covariates include a dummy variable taking value one for those who did not answer the question assessing risk tolerance, and a dummy variable taking value one for those who did not declare their income. Estimates use sample weights. Standard errors are clustered by province of respondent's residence. Columns (3) is conditioned on who does not use robo-advisors (placebo). The first set of regressions includes only province fixed effects, the second set includes bank×province fixed effects. Statistical significance levels: *** p<0.01, ** p<0.05, * p<0.1.

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