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Correcting Present Bias in Saving Decisions with FinTech

Antonio Gargano, Alberto G. Rossi

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Antonio Gargano[†]
University of Melbourne and
University of Houston

Alberto G. Rossi[‡]
Georgetown University

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Present biased and time-inconsistent preferences are often pointed to as the main psychological reasons behind individuals' under-saving. In this paper, we study the effectiveness of soft, self-designed commitment devices, i.e. saving goals, in increasing individuals' savings using data from a FinTech App. We establish that setting goals increases individuals' saving rate and show that the effect is causal using a difference-in-differences identification strategy that exploits the random assignment of users into a group of beta-testers that can set goals and a group of users that cannot. We also show that the increased savings within the App do not come at the expense of reduced savings outside the App. We explore the economic channels of our results by matching App user survey responses to their behavior and highlight the importance of a *monitoring channel*, consistent with models where agents experience disutility from falling short of their goal.

Keywords: FinTech, Goal Setting, Individual Investors, Saving Behavior

"Ignoranti quem portum petat nullus suus ventus est"

"If one does not know to which port one is sailing, no wind is favorable"

Lucius Annaeus Seneca

The economics and finance literature has uncovered a large numbers of behavioral biases in individuals' investment and saving decisions.[1] Much less is known about how to correct them on a large scale.[2] In this paper we provide evidence that FinTech Apps can reduce the incidence of present bias in consumption-saving choices, arguably the most crucial decision when it comes to wealth accumulation.

Present biased and time-inconsistent preferences (Cohen et al., 2020) are often pointed to as the main psychological reasons a large majority of individuals does not save enough to withstand adverse income shocks and is unprepared for retirement.[3] Theoretically (Thaler and Shefrin, 1981; Laibson, 1997; O'Donoghue and Rabin, 1999), it should be possible for individuals to overcome their present biases using commitment devices, which vary in terms of whether individual can deviate from them— *hard* versus *soft*—and whether they are *self-designed* by the users or *pre-designed* by experts.

Hard commitment devices generally entail penalties for not following the planned course of action, such as withdrawing funds from a savings account before a pre-established horizon, see Ashraf, Karlan, and Yin (2006). Less is known about soft commitment devices (Beshears, Milkman, and Schwartzstein, 2016), where individuals face no penalties when deviating from their plan. The key trade-off between these two commitment devices is that soft commitments are more scalable and easier to administer compared to hard commitments, especially in non-experimental real life settings. At the same time, the lack of monetary costs associated with non-compliance may make soft commitments less effective (DellaVigna and Malmendier, 2006).[4]

For the most part, the economics literature has shown the effectiveness of pre-designed saving goals (Bryan, Karlan, and Nelson, 2010). The psychological literature, on the other hand, has highlighted

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[1]See, among others, the disposition effect (Shefrin and Statman, 1985; Odean, 1998), overconfidence (Barber and Odean, 2001), familiarity bias (Huberman, 2001), endowment effect (Anagol, Balasubramaniam, and Ramadorai, 2018), inertia (Madrian and Shea, 2001), and naive diversification (Benartzi and Thaler, 2001).

[2]See nudges and defaults (Thaler and Sunstein, 2009; Madrian and Shea, 2001; Thaler and Benartzi, 2004; Brown and Previtero, 2020; Medina and Pagel, 2021), reminders (Karlan et al., 2016), policy interventions (Gargano and Giacoletti, 2021) and robo-advising (D'Acunto, Prabhala, and Rossi, 2019; Rossi and Utkus, 2020).

[3]See, among others, Banks, Blundell, and Tanner, 1998; Bernheim, Skinner, and Weinberg, 2001; and Lusardi and Mitchell, 2007. See Kuchler and Pagel (2021) for evidence of present bias on debt repayment.

[4]Bénabou and Tirole (2004) and Hsiaw (2013) show that soft commitments can be effective if individuals experience disutility from falling short of their goals.

that a key aspect in the effectiveness of goal-setting is the appropriateness and correct design of the goal—see Locke and Latham, 2002 and Locke and Latham, 2006—and it is not clear whether individuals are able to create well-designed saving goals for themselves. Answering this question is crucial given that self-designed goals are more practical so much that a large number of banks and FinTech firms are now offering goal setting tools for saving to their customers—see Figure A.1 for some examples.

In this paper, we study the effectiveness of *soft, self-designed* commitment devices in saving decisions using data from an App developer that provides its users with simple budgeting solutions in the form of saving goals. We complement the administrative App data with a survey administered on a sample of App users to uncover the economic mechanism underlying individuals' goal-setting choices.

Because the saving goals we study are self-designed, we start by analyzing their characteristics and assessing the extent to which they are realistic, achievable and congruent with finance theory. First, savings goals are generally short-term, in that the vast majority of the goals have horizons of one year or less. Second, savings goals are generally small, less than €2,500, and we observe evident bunching at whole amounts such as €1,000, €2,000, €5,000, €20,000, etc. Finally, consistent with the view that users understand time value of money and perceive stocks as safer in the longer run, we find a positive relation between goal horizon and both the goal amount and the risk of the chosen investment fund. In both cases, the relation is concave, suggesting that neither quantity increases proportionally with the horizon of the goal.

Our central findings pertain to the relation between goal-setting and saving behavior. We start with baseline *user-level* panel regressions that control for individual-specific and time fixed-effects. These results indicate that individuals who set goals save an additional €345 per year, on average. Before the introduction of the goal-setting feature, the same individuals were saving €379 per year on the App, suggesting an economically very large increase in savings of 345/379= 91%. When we decompose the overall savings into its parts, i.e., withdrawals and deposits, we find the additional savings are mainly driven by an increase in the deposit rate and not a decrease in the withdrawal rate.

The limitation of the *user-level* results is that individual-specific time-varying shocks could explain the differential behavior of goal-setters compared to non-goal setters. In this respect, our setting is

unique in that we can compute results at the *user-account-level*, which allow us to compare the saving behavior of users who set goals to the saving behavior of the *same* user in other accounts where they do not set goals, effectively controlling for individual time-varying shocks. This empirical strategy suggests even stronger effect of goal setting that range between €322 and €658.2 per year, depending on the specification. In line with the baseline results, these findings also suggest that goal-setting increases individuals' propensity to save and leaves users' withdrawal activity unchanged.

We augment these results with dynamic specifications that study the effectiveness of goal setting over time. Users save substantially more in the first month after adopting goal-setting, where additional savings exceed €30 per month. Over time, however, the additional savings decrease and stabilize to approximately €15 euro per month. This indicates that the initial enthusiasm induced by the new saving tool explains part, but not the full extent, of the savings differential we document in the baseline results. Moreover, consistent with our baseline results, the effect seems to be fully driven by deposits and not by withdrawals, as the latter do not change at any horizon.

A limitation of the *user-account-level* results, however, is that individuals may substitute their savings from the account without goal-setting to the account with goal-setting after choosing to use this novel feature. Ideally, one would want for some individuals to be randomly assigned to be goal-setters and others to be randomly assigned to be non-goal-setters for an extended period, i.e. several months or years. Fortunately, while we do not have access to such randomized experiment, we do have access to something very similar. The App developers activated the goal-setting feature for 122 individuals (beta testers) 50 days before the goal-setting feature was rolled-out to the whole population. This allows us to estimate a difference-in-differences model where the beta testers are the treated group and the rest of the users of the App are the control group. This identification strategy estimates whether goal-setting would increase investors' saving over time, if it were deployed on the broader population at large. The results show that those who have access to the goal-setting features of the App save significantly more than those who don't, confirming our baseline results.

To rule out that the increased savings inside the App are a substitute for the savings outside the App, we explicitly ask the App users in our survey how they have changed their saving habits outside the App after its adoption and show that, if anything, they have increased their saving outside the app.

We also re-estimate our baseline findings on those individuals who declare they do not save outside the App and show that the results are very similar to the ones we find for the overall population.

In the third part of the paper we explore the economics of our findings and show that *monitoring* is the crucial mechanism underlying the effectiveness of goal-setting for saving, consistent with the theoretical predictions in Bénabou and Tirole (2004) and Hsiaw (2013). We first show that, when surveyed, individuals identify the ability to track their progress towards a goal as the most motivating aspect of setting a goal. Other aspects such as the nature of the goal or the presence of a deadline are less important.

Second, we relate users' saving behavior to the characteristics of the goals they set such as type, horizon, and goal amount. When we group goals based on type (*leisure*, which includes Hobby and Travel; *durable*, which includes Car and House; and *generic* saving) we find no significant differences, suggesting that the nature of the goal does not matter. We also find individuals save significantly more for shorter goals (less than or equal to one year), consistent with the shorter horizon making it easier for individuals to monitor their progress.

Third, we shed light on the factors affecting the probability of achieving goals as well as the dynamics of saving for goals. While goal-setting increases savings, it does not imply that users reach their goals. Indeed, we find that only 30% of the goals are achieved, while the rest are either closed or remain overdue but still active. The specificity of the goal does not increase the completion rate. On the contrary, specific goals such as hobby, travel, car and house categories all have a probability of success 10% lower than the "generic savings" category.[5] We also find that short-term and small goals are the ones most likely to be achieved. Taken together these results reinforce the idea that the increase in savings we document in our main results is not due to the nature of the goal, but rather to users' ability to monitor their progress towards their goal.

In the final section of the paper, we quantify the economic effects of goal-setting in reducing the under-saving associated with present biased preferences. For these computations, we use three quantities: 1) individuals' saving rate before adopting goal setting; 2) the implied saving rate associated with saving goals; and 3) the saving rate users achieve when they use goal-setting, which is the result

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[5]To make sure our findings are not an artifact of the coarse categories set by the App, in a robustness section we confirm these results using the name of the goal the users assign to each goal.

of planning and having the freedom to deviate from the original plan. We interpret the difference between the saving rate implied by goals and the saving rate when not setting a goal as the potential effect of goal setting in increasing savings rate. We interpret the difference between the saving rate implied by the goals and the saving rate obtained with goal-setting as the reduction in saving (leakage) individuals experience because of the freedom associated with soft commitments. Finally, we interpret the difference between the saving rate associated with goals and the saving rate without goals as the realized effect of goal setting in reducing investors' hyperbolic discounting.

The median individual saves 1% of her net income when she does not set goals. The planned percentage savings associated with goals equal 4.6% of her net income. Finally, the percentage savings realized when setting goals equal 2.4% of her income. These differences in savings rate highlight that there is substantial leakage associated with the soft commitments individuals engage in. They also show that goal setting can help individuals increase their baseline savings rate.

1   Related Literature

This paper contributes to the very recent and fast-growing literature on Financial Technology (FinTech) and household welfare. FinTech encompasses a broad range of new technologies that seek to improve and automate the delivery and use of financial services (see Philippon, 2016 and Das, 2019 for a review of the literature). A recent strand of the literature shows that FinTech can help households improve their trading performance and asset allocation (e.g. Gargano and Rossi, 2018; D'Acunto, Prabhala, and Rossi, 2019; Rossi and Utkus, 2020; and D'Acunto and Rossi, Forthcoming), to reduce overspending (D'Acunto, Rossi, and Weber, 2019), to save on bank fees (Carlin, Olafsson, and Pagel, 2019; D'Acunto et al., 2019; and Loh and Choi, 2020) and to better conduct house searches (Gargano, Giacoletti, and Jarnecic, 2019).[6] At the same time, another strand of the literature highlights the pitfalls generated by the introduction of new technology. For example, Fuster et al. (2018) find that Black and Hispanic borrowers are disproportionately less likely to gain from the introduction of machine learning tools to predict creditworthiness, while Di Maggio and Yao (2020) find that FinTech borrowers are significantly more likely to default than their peers borrowing from traditional financial

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[6]More broadly, Agarwal et al. (2020) and Agarwal, Yeung, and Zou (2019) show the positive effect of Financial Technology on entrepreneurship and business creation.

institutions. Laudenbach, Pirschel, and Siegel (2018) find that borrowers who speak directly with a bank agent are significantly less likely to default. We contribute to this literature by showing the benefits of financial technology in the savings domain, which still remains largely unexplored.

The effectiveness of hard commitments, which either entail a monetary penalty for deviating from the plan of action or restrict the set of future available options, is supported by evidence across a broad range of domains. For example, these devices have been shown to increase agricultural input use (Duflo, Kremer, and Robinson, 2011), preventative health investment (Dupas and Robinson, 2013), and chances of successful smoking cessation (Giné, Karlan, and Zinman, 2010). In the saving domain, the focus of our study, Ashraf, Karlan, and Yin (2006) run an experiment in the Philippines and show that individuals with higher hyperbolic discounting are more likely to open a savings product restricting access to deposits which in turn increases their saving. Beshaers et al. (2020) study the effectiveness of different schemes and find that higher early-withdrawal penalties attract more commitment account deposits. On the other hand, the evidence on soft saving commitments, where individuals face no penalties when deviating from their plan, is more limited. These commitments are more scalable and much simpler to administer compared to hard commitments, however, the lack of monetary costs associated with non-compliance may make soft commitments less effective (DellaVigna and Malmendier, 2006). It is not clear whether individuals are able to create well-designed saving goals for themselves. Breza and Chandrasehkar (2019) run an experiment in rural India and show that individuals save more when information about the progress toward their self-set savings goal is shared with another village member who act as a monitor. On the other hand, John (2020) shows that imperfect knowledge about their preferences lead individuals to select into incentive-incompatible saving commitments, which reduce their welfare. We contribute to this literature on commitment devices by providing evidence on *soft*, *self-designed* commitments that can administered on a large scale using FinTech Apps.

2 The Setting

This section provides a description of the App featured in this study and the survey we conducted on a random sample of its users.

2.1 The Saving App and the Introduction of the Goal-Setting Features

The data used in this study were generously shared by the Italian asset manager AcomeA that developed a saving App called Gimme5. Gimme5, launched in 2014, was initially designed as a digital piggy-bank that allowed its users to save small sums of money, such as 5 euros, at a time—hence the name "Gimme5." At the time of sign-up, individuals face zero activation costs and no annual fees.[7] After signing up for an account, investors can start saving by depositing as much money as they wish, whenever they want, much like a checking/savings account. Unlike checking/savings accounts, however, Gimme5 users are allowed to invest their savings—however small they are—in a variety of investment funds that vary in their risk-return profiles. As of 2019, individuals could invest their wealth in as many as 14 funds, some of which are actively managed and therefore charge management fees. Table A.1 displays the annualized return, volatility and Sharpe ratio of each fund computed over the Jan-2015 to Dec-2019 period.

In October 2017, the App introduced a goal-setting feature by which users can set one or multiple saving goals. Since then, when setting a goal, users are prompted to choose the investment objective, categorized in six broad categories: hobby, travel, other, car, house and general savings. The users are also required to choose an investment horizon and a target amount. Figure 1 presents screenshots of the App over these phases. The first step (Subfigure A) prompts the user to name the target. The second (Subfigure B) asks the user to choose between the six categories: Hobby (Tempo Libero), Travel (Viaggi), Other (Altro), Car (Veicoli), House (Casa) and Savings (Risparmio). The third (Subfigure C) prompts the investor to choose a target amount and a deadline to reach the target. Finally, the fourth (Subfigure D) asks the investor to associate the target with an image. The App is by no means unique or specific to the Italian setting. In recent years, many banks like Chase, Wells Fargo and financial aggregators in the US such as MINT.com have implemented saving goal tools that are virtually identical in structure and features as the one we describe here—see Figure A.1 for some examples.

After choosing the target, the investor chooses which mutual fund she would like to invest in. The App features three baseline funds, displayed in Figure 2 (Subfigure A). Their names are Prudent (Pru-

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[7]The only fee they face relates to the withdrawal of funds. Users are charged a €1 withdrawal fee, irrespective of the amount withdrawn.

dente), Dynamic (Dinamico), and Aggressive (Aggressivo), and they are characterized by increasing levels of risk. The users can choose among 14 total funds, by clicking on the link that states "Full List of Funds" (Elenco Completo dei Fondi), but the majority of the users selects the baseline funds.

After the goal and the fund(s) are chosen, the investor can deposit money whenever she likes. The App features an intuitive interface that shows the user where she stands in achieving the goal. An example is reported in the two screenshots—Subfigures B and C—of Figure 2. In this example, the user has budgeted €3,000 for a vacation in the US and has 568 days to achieve the deadline. As of the day of the screenshot, the person has saved only €10. The graphics makes extremely salient how far the user is from the target. The user can simply click the icon with the pig with a 5 written on it at the bottom of the screen to add funds to the account and reach the goal. The icon is referred to as the "Joink" icon. Once the user pushes the Joink button, she is taken to a different page where she can choose how much to deposit for that goal, the default being €5.

Crucially, after the introduction of these goal-setting features, users could choose to continue using the App as a digital piggy-bank with no goals, use only the newly introduced goals, or use both features of the App at the same time.

2.2   The Survey

We complement the administrative data with a survey administered on a sample of App users.[8] Matching individuals' actions on the App to their survey responses is crucial for us to uncover the economic mechanism underlying individuals' choices, see D'Acunto, Malmendier, and Weber (Forthcoming), Coibion et al. (2020), Coibion, Gorodnichenko, and Weber (2019), Giglio et al. (Forthcoming), and Giglio et al. (2021). The survey was administered by email on a random sample of 5,000 App users over the week of March 15-21, 2021. The number of respondents was 814, for a response rate of 16.3%.

The survey comprises four sections. In the first, we elicit information we cannot observe from the administrative data. For example, we ask App users how much they were saving outside the App before and after its adoption. We also ask them what are the main accounts they use to save and invest their wealth, that is, savings accounts, brokerage accounts, retirement account, etc.

The second and third sections of the survey focus on individuals' motivations for creating targets

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[8]We report the translated survey in the the last section of the Online Appendix.

within the App and using the Joink feature. More precisely, for those who have created at least one target, we ask what they believe is the most motivating aspect of goal-setting, and what are the main reasons they did (or did not) achieve a target in the past. Finally, we elicit—in a number of questions—what is the underlying psychological motivation for using the Joink feature.

In the last part of the survey, we measure users' patience, risk-aversion and financial literacy following standard questions in the literature—see Lusardi and Mitchell (2017), Falk et al. (2018), and D'Acunto, Rossi, and Weber (2019). We also ask respondents for their level of education, and net income. Figure A.2 reports a summary of the survey responses regarding financial literacy, patience, risk propensity, education and monthly income.

3 Data and Self-designed Goal Characteristics

Next we describe the main data sources and report the summary statistics for the key variables of interest. All information was anonymized by the company to guarantee user privacy.

3.1 Data Sources

The data is in the form of 4 SQL tables named *Users*, *Goal Information*, *Deposits and Withdrawals*, and *Investment Vehicle*. The main features of each table are described below.

Users. This table contains information on the 47,643 users who created a profile on the App since its inception. The main variables contained in this table are the dates of opening and closing for every savings account created within the App by each user.[9] Additional information includes users' age, gender, and enrollment date—the date on which the profile was created—and the locations where the users reside, where they where born, and other questions related to Know Your Customer (KYC) compliance.

Goal Information. This table contains information on all the goals set by each user in each savings account. For each target we observe the inception of the goal, the deadline for the goal, the amount the user aims to save, the purpose of the goal—categorized in the six broad categories: hobby, holiday, other, car, house, and "generic savings"—and the name each individual assigns to each goal she creates.

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[9]Users can create multiple savings accounts within the App to invest their savings across different mutual funds.

Deposits and Withdrawals. This table contains information on all the deposits and withdrawals associated with each user at the daily frequency. For each transaction, we have information on what account and/or goal it is associated with, as well as the amount withdrawn or deposited.

Investment Vehicle. This table contains information on the name and identifier of the mutual fund associated with each savings account of the user.

3.2 Summary Statistics

Table 1 reports the main cross-sectional summary statistics, computed in two steps. We first compute the value of each variable at the user level and then report the distribution of the variable across all users. For each variable, we report the number of observations used in the second step of the computations, the mean and standard deviation of each variable, as well as the $1st$, $25th$, $50th$, $75th$, and $99th$ percentiles.

Panel A shows that 81% of the users are males, suggesting that, in Italy, women are either less targeted by Financial Apps or are less interested in these tools. Users are rather young, with an average age of 36. Panel B reports results on App usage. Here the summary statistics are computed using individuals that have transacted at least once on the platform, which are 27,439. As of November 2019—the date when we received the data— the average user had used the App for 11.50 months. Active users interact with the App often and the average size of each deposit is €35.35, in line with the spirit of the App of promoting savings in the long-run by helping users save small amounts at a time.

Panel C reports facts regarding the number of accounts and targets associated with each user. Turning to targets, 27 percent of the users had created savings goals as of November 2019, indicating that the majority of users used the App as a simple "Digital Piggy Bank" without setting specific goals for their savings. Individuals like to set one or—at most—two targets at a time (the average is 1.43). As of November 2019, when we received the data, the average investor had a little less than one target open and the average number of targets closed and not completed was equal to 0.3. Finally, the number of targets completed equaled to 0.28 per user.

3.3 Saving Goals

Because the saving goals we study are self-designed, their analysis can offer a window into investors' savings preferences and beliefs, and allow us to assess the extent to which they are realistic, achievable and congruent with finance theory.

The first two panels of Figure 3 report the histograms of target horizons. To improve the legibility of the graph, we split the histogram into two plots, the first associated with horizons shorter than 1,000 days, and the second associated with horizons longer than 1,000 days. Overall, individuals set savings goals that are rather short-lived. The majority of the goals have horizons of less than one year and a large number of goals have horizons of exactly one year. Furthermore, we observe clear bunching of the distribution at the one, two, three, all the way to the 10-year horizon.

The second two panels of Figure 3 report histograms of goal amounts. Once again, individuals set goal amounts at round numbers. The majority of the goals are small, less than €2,500. For larger amounts, the distribution has evident bunching at €1,000, €2,000, €3,000, €5,000, €10,000, €20,000, and €50,000.

The bottom-left panel of Figure 3 focuses on the 14 mutual funds from which investors can choose to invest their savings. We classify the funds in three categories on the basis of the type of fund: Fixed-income, Balanced and Equity—see Table A.1 for details. As shown in the bottom-left panel, the majority of investors (55%) chooses balanced funds, followed by fixed-income and equity funds that are selected by 32% and 13% of the users, respectively. Unconditionally, individuals avoid exposure to pure equity funds, suggesting a relatively high degree of risk-aversion and low trust in the stock market (Guiso, Sapienza, and Zingales, 2008).

The bottom-right panel of Figure 3 focuses on goal categories. Half of the individuals set goals that do not fall naturally into specific categories and are therefore assigned a generic category named "Savings," suggesting that the nature of the goal may not be crucial to the App users—an aspect we study at great length in Section 5. Turning to the other categories, "Travel" is the most common, which comprises 20% of the targets, followed by "Car," "Hobby" and "House," which each make up a little less than 10% of the categories.

Next, we relate the horizon of each target to the target amount and the investment risk using a

nearest neighbor estimator in Figure 4. We find a positive and monotonic relation between target horizon and amount (Panel A). Quantitatively, users budget approximately 1,000 days to save €5,000; 2,000 days for €10,000. The relation then becomes more concave, indicating that individuals budget proportionally more time to save additional amounts. We also find an increasing and concave relation between target horizon and investment risk (Panel B). As the investment horizon increases users choose riskier funds, supporting the idea they believe stocks are a better investment for the long-run compared to fixed-income securities (Siegel, 1998).

4 The Effects of Goal-Setting on Saving Behavior: Baseline Results

Results from the psychology literature (Locke and Latham, 2002, 2006) suggest that goal-setting should have a positive effect on saving if setting goals allows individuals to remain focused on the saving objective and deadline, and allows investors to track their performance against it. In addition, several theoretical models developed in economics (Hsiaw, 2013; Bénabou and Tirole, 2004; Beshears, Milkman, and Schwartzstein, 2016) predict that present-biased individuals set goals as a soft commitment device to overcome their self-control problems. Such goals provide internal motivation because individuals derive utility from comparing outcomes to goals.

On the other hand, goals could be counterproductive and have a discouraging effect if they are too ambitious and unrealistic—see, for example, John (2020). This concern is particularly relevant in our setting as individuals choose their goal characteristics, such as horizon and amount and the goals we study are non-binding commitments.

In our baseline specification, we estimate a simple panel regression of the following form:

$$M\_Net\_Deposits_{i,t} = \alpha_i + \alpha_t + \beta\ Target\_Dummy_{i,t} + \epsilon_{i,t}, \tag{1}$$

where $M\_Net\_Deposits_{i,t}$ are the monthly net deposits (deposits minus withdrawals) of individual i during month t, $Target\_Dummy_{i,t}$ is an indicator variable equal to "0" if the user did not set any goals in her account at time t and "1" if she set at least one goal at time t. The coefficients α_i and α_t identify individual and time effects, respectively. The standard errors are double-clustered at the

user and month levels.

The coefficient of interest is β, which identifies the relation between the change in monthly savings when users engage in goal-setting, controlling for individual-specific characteristics and time-effects. The results, reported in the first column of Table 2, indicate a large effect of goal-setting on saving behavior. The coefficient equals 28.74, with a t-statistic of 16.37, indicating that those individuals who set goals on average saved an additional $28.74 \times 12 = €345$ per year. The estimated constant (which corresponds to the average of the individual fixed-effects) equals 31.61, indicating that individuals save approximately $31.61 \times 12 = €379$ on the app when they do not set goals. By comparing the coefficient on the constant (31.61) and the one on $Target\_Dummy$ (28.74), the percentage increase in net savings associated with adopting a target is $28.74/31.61 = 91\%$, suggesting that self-designed soft commitments can improve savings.

In the second and third columns of Table 2 we repeat the analysis, but focus on users' deposits and withdrawals, respectively. The coefficient on the $Target\_Dummy_{i,t}$ suggests that goal-setters save an additional €34.56, compared to those who do not set goals. The coefficient estimate for the constant suggests that the average investor that does not set goals saves €41.06 per month. The effect of goal-setting is less pronounced for withdrawals. Goal-setters withdraw an additional €5.60 compared to those who do not set goals, but the economic magnitude of the effect is rather small. By comparing the results for Net Deposits, Deposits, and Withdrawals, it is clear that goal-setters deposited more in their accounts and also withdrew more. The additional withdrawals, however, are only a fraction of the additional deposits. As a result, the change in net deposits is strongly positive and significant.

4.1 Results at the User-Account Level

So far the results reported compare, at the user-level, savings patterns when people set goals compared to when they don't—controlling for their fixed characteristics (fixed-effects) as well as aggregate time-shocks (time-effects). One limitation of these results is that time-varying individual-specific shocks could explain the differential saving behavior of goal-setters compared to non-goal-setters. Our setup is unique in this respect, in that it allows us to estimate results at the user-account level, that is, we can compare the behavior of a user who sets goals in one (or more) of her savings accounts, to the

behavior of the *same* user in other savings accounts where she did not set goals, effectively allowing us to control for individual-specific time-varying shocks. We compute these estimates using the panel regression:

$$M\_Net\_Deposits_{i,j,t} = \alpha_i + \alpha_t + \beta \ Target\_Dummy_{i,j,t} + \epsilon_{i,j,t}, \qquad (2)$$

where $M\_Net\_Deposits_{i,j,t}$ are the net deposits of user i in account j at time t; $Target\_ Dummy_{i,j,t}$ is dummy variable equal to 1 if account j associated with user i at time t is characterized by goal-setting, and zero otherwise.

The results of Specification 2 are reported in Table 3. In Panel A, we use all the individual-account-time triplets to estimate our coefficients. In Panel B, we repeat the analysis, but only focus on those individual-account-time triplets where a given user had at least one goal-setting account and one non-goal-setting account at each point in time. In both specifications, the coefficient of interest β measures the differential saving between accounts with targets and accounts without targets.

In all cases, the coefficient estimates are strongly positive and significant. In the first column of Panel A, the coefficient estimate on $Target\_Dummy_{i,j,t}$ equals 26.84, while it equals 54.85 in the first column of Panel B. A coefficient of 54.85 implies a differential saving of $54.85 \times 12{=}€658.2$ per year in accounts with targets compared to accounts without targets, for a user with both at the same time.

The second and third columns report results for Deposits and Withdrawals. Across both Panels A and B, we find that the whole effect arises from deposits rather than withdrawals. The coefficient on $Target\_Dummy_{i,j,t}$ for Deposits (column 2) is 29.40 and 55.87 in Panels A and B, respectively, both strongly statistically significant, with t-statistics in excess of 15. On the other hand, the coefficients associated with $Target\_Dummy_{i,j,t}$ for Withdrawals are small and insignificantly different from zero. Overall, the results reported in Table 3 suggest that setting goals increases individuals' propensity to save, but does not increase users' withdrawal activity.

4.2 Goal-Setting and Persistence of Saving Behavior Over Time

Our results reported so far could potentially be explained by a "new toy" effect, whereby individuals saved more at the beginning, but stopped saving as they grew accustomed to the new features of

the App. We can test how individuals save over time as they adopt the new goal-setting features introduced in the App by estimating a modified version of Equation 2, as reported below:

$$M\_Net\_Deposits_{i,j,t} = \alpha_i + \alpha_t + \sum_{s=-6}^{18} \beta_s \, Target\_Dummy_{i,j,s,t} + \epsilon_{i,j,t}. \qquad (3)$$

The only difference between Equation (3) and Equation (2) is in the definition of $Target\_Dummy_{i,j,s,t}$. In Specification 3, $Target\_Dummy_{i,j,s,t}$ equals 1 only if individual i used goal-setting in account j for the $s-th$ month in the calendar month t. In the specification above, s ranges from -6 to 18. The β_s coefficients in Specification 3 therefore decompose the effect of β in Specification 2. The coefficient estimates for Net Deposits, Deposits and Withdrawals, corresponding to the more restrictive results contained in Panel B of Table 3, are reported in Figure 5.

The results suggest two findings. First, the effect is strongest over the first six months, where it peaks at €45 per month; and it then decreases and asymptotes to approximately €10-€15 per month, suggesting that initial enthusiasm explains part of the increase in savings, but not the full saving differential. Second, the effect seems to be fully driven by deposits: none of the effect is driven by withdrawals that never differ from zero at any horizon.

The results reported in Figure 5 mix the extensive and the intensive margins. At one extreme, it could be that all individuals save a lot more in the initial months after setting a goal and reduce their monthly savings over time. At the other extreme, it could be that all individuals save a lot initially, but as time goes by only a small percentage of individuals maintain high savings while the other users stop saving altogether. Both hypotheses, as well as the intermediate cases, are consistent with the results in Figure 5.

To address whether the effect is mainly driven by the intensive margin or the extensive margin, we estimate two variations of Equation (3). In the first, we replace $M\_Net\_Deposits_{i,j,t}$ with $IND_{i,j,t}$, an indicator variable equal to 1 if the monthly net deposit of individual i in account j is positive in month t. In the second we replace $M\_Net\_Deposits_{i,j,t}$ with $M\_Net\_Deposits^+_{i,j,t}$, which denotes the monthly net deposit (in €) by user i in account j at time t, conditional on $IND_{i,j,t}$ being equal to 1. The β coefficients in the first specification measure the increase in probability of having positive net deposits, while the β coefficients in the second specification measure the increase in amount deposited,

conditional on the user depositing wealth in the App on a given month. The results, reported in Figure 6, highlight that goal-setting increases both the intensive and extensive margins of saving. The probability of depositing money on the App increases by 45% on the first month after setting the goal, but the effect is reduced as the horizon increases. The effect stabilizes to approximately 20%, 12 months after the goal is set. The intensive margin results are similar. Conditional on depositing money on the App, users increase their net deposits by €20 the first month after setting the goal and the increase in saving monotonically decreases and stabilizes to approximately €5, 12 months after the goal is set.

4.3   Identification Strategy Results

A limitation of the *user-account-level* results is that individuals may substitute their savings from the account without goal-setting to the account with goal-setting after choosing to use this novel feature. Ideally, one would want for some individuals to be randomly assigned to be goal-setters and others to be randomly assigned to be non-goal-setters for an extended period, i.e. several months or years. Fortunately, the App developers implemented something very similar to a randomized control trial: they activated the goal-setting feature for 122 individuals 50 days before they made it available to the overall population. These users were unaware of being selected for the trial. The main difference between the procedure implemented by the firm and a standard randomized control trial is that the number of individuals selected for the trial is probably smaller than we would have preferred and that the company did not store the details of the formal randomization scheme they used. For example, we do not know if they stratified the sample. The 50-day trial duration is another limitation.

Nevertheless, this natural experiment implemented by the firm allows us to estimate a difference-in-differences model where the beta testers are the treated group and the remaining population of App users are the control group. This identification strategy estimates whether goal-setting would increase investors' saving over time, if it were deployed on the broader population at large. Our specification reads as follows:

$$M\_Net\_Deposits_{i,j,t} = \alpha_i + \alpha_t + \beta\ Treated_{i,t} + \epsilon_{i,j,t}, \tag{4}$$

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where all quantities are defined as in Equation (2) except for $Treated_{i,t}$ which is equal to 1 for the 122 beta testers for the 50 days (from August 1, 2017 to September 20, 2017) over which they had access to the goal-setting features of the App while the rest of the App users did not.

Note that, because we estimate everything at the monthly level and we seek to be as conservative as possible, the $Treated_{i,t}$ dummy is equal to 1 only for the month of August 2017 and not September 2017, because all the App Users had access to the goal-setting features of the App over the last 10 days of September. Note also that, unlike the results estimated in Section 4.1, here the effect is likely to be much smaller, because the treated group only gained access to the goal-setting features, but was not required to use them.

The results for net deposits are reported in Panel A of Table 4. The estimate suggests that those who had access to the goal-setting features of the App saved, on average, €5.22 additional per month, or €62.64 per year. The results in column 2 show individuals deposited €5.41 per month, significant at the 1% level. Finally, the results in column 3 indicate that those investors who used goal-setting also withdrew more, but the coefficient estimating the differential is economically small—only 68 cents per month (though statistically significant).

Panel B of Table 4 repeats the analysis focusing only on the individuals who saved with and without targets at the same time. The results are very much in line with the ones reported in Panel A, but they are slightly smaller. For example, the coefficient on the treated dummy is 3.67 in first column of Panel B versus 5.22 in the first column Panel A.

As mentioned above, the company did not store the details of the randomization algorithm they implemented to select the beta testers. It is therefore not guaranteed that the beta testers' activity and demographic characteristics match the ones of the rest of the App users. We analyze this in Table 5. In order to capture users' activity, we use the following variables: $Tenure$, the number of months elapsed from the opening of user's first account to the July 2017—the beginning of the beta-testing period; $N.\ Accounts$ and $Net\ Inflow$, which denote the number of accounts opened and the monthly average net deposit into the App, computed from January 2017 to July 2017. To capture user risk-preferences and demographic characteristics, we use: $Risk$, the average annual standard deviation across the funds used by the user; $Gender$, a dummy variable equal to one if male; and Age, measured

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as of July 2017. Panel A displays the characteristics of the beta testers while Panel B focuses on the rest of the users in the sample. For this second sample, we also report the t-stats associated with the tests of the equality of means between beta-testers and non-beta-testers. The results indicate that the two groups of users are rather similar. Beta-testers and non-beta-testers are statistically indistinguishable in terms of all the characteristics, except for $Tenure$ and $Net\ Inflow$. Beta testers are statistically more experienced in that they have been on the App for longer (564 months against 436) and have saved more on average—€209 against €126—from January to July 2017. In order to account for such differences and create a sample of users more comparable with the beta testers, we use a nearest neighbor propensity score matching procedure. For each beta-tester, we choose the closest match based on the six variables described above.[10] Panel C shows the characteristics of the matched sample of users. All the t-tests are insignificant, indicating that these matched users are indeed statistically indistinguishable from the beta testers.

Even though the results in the Table 5 do not highlight major differences in user-characteristics between beta-testers and non-beta-testers, in Table 6 we re-estimate difference-in-differences framework in Equation (4) using the matched sample described above.[11] The results highlight the following facts. First, even though the sample has dramatically dropped in size, the coefficients remain statistically significant. Second, the coefficient estimates are now larger, suggesting that removing some the confounding factors, if anything, increases the estimated the effect of goal setting on saving behavior. For example, the coefficient on $Treated_{i,t}$ equals 11.47 in the first column of Table 6, suggesting that the causal effect of introducing goal setting increases savings by €11.47 per month, or €137.64 per year. The results in Panel B of Table 6 also show an economically large effect of the introduction of the goal-setting feature on the population of individuals who save with and without goals throughout the sample.

It is rather impressive that we obtain such statistically significant results, even though we had only 122 beta testers in the sample and they were treated for only a little over a month. The strength of these identification results suggests that the baseline results reported in the previous section are unlikely to capture severe selection effects.

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[10]In Table A.2 we report results when matching each beta tester with the closest two or ten users.

[11]In Table A.3 we report results when matching each beta tester with the closest two or ten users in Panels A and B, respectively.

In Section 5, we estimate the differential effect of goal setting across different types of goals and for different types of investors. Unfortunately, data limitations do not allow us to estimate these results in the identification setting described here. We therefore revert to the baseline specifications described at the beginning of Section 4.

4.4 Ruling Out Substitution Between Saving Within and Outside the App.

A possible concern with our results is that individuals could perceive saving within and outside the App as substitutes and could therefore decrease their savings outside the App when they start using the App. Unfortunately, we cannot rule out this mechanism with the administrative data, as we do not have information on deposits and withdrawals on accounts other than the ones on the App.

To circumvent this limitation, we included in our survey specific questions related to individuals' saving outside the App, before and after its adoption. In particular, we ask three questions. The first asks users whether they increased, decreased or left unchanged their savings rate outside the App after its adoption. The results are reported in Panel a) of Figure 7. The vast majority of the respondents (51.2%) say they have not changed their savings outside the App. A significant number (35.0%) state they increased their saving outside of the App. Finally, only a small minority of individuals (13.8%) state they decreased their savings outside the App.

In two additional survey questions, we explicitly ask the respondents for their saving rate before and after adopting the App and gave them five options to choose from: 1) €0; 2) €1-€49; 3) €50-€100; 4) €101-€150; 5) €150+. As shown in Panel b) of Figure 7, individuals increased their savings outside the App after its adoption. The red bars—denoting saving after App adoption—are higher than the blue bars—denoting saving before App adoption—for all response categories except for the €0 option. This entails that the entire distribution of saving outside the App increases after individuals sign up, ruling out any potential substitution effect between saving inside and outside the App.

We also perform several additional quantitative tests to rule the possibility of a substitution effect between saving inside and outside the App after adopting goal-setting. We report them in Table A.4. In the first column, we re-estimate regression specification (1) only on the survey respondents and find a very similar effect as on the full sample (column 1 of Table 2). In the second column, we restrict

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the sample to those survey respondents who state they have no savings outside the App and show the results are virtually identical.

In the last three specifications, we interact the target adoption dummy with three groups of users. The first comprises users who do not save outside the App. For these users the substitution channel cannot be present by construction, we therefore expect a lower increase in saving after adopting the target (negative interaction coefficient) if a substitution effect was in place among the rest of the App users. The second group comprises users who state they do not change their saving rate outside the App after its adoption. Also for these users, the substitution effect should be zero and we should expect a negative interaction coefficient. Finally, the third comprises users who state they reduce their savings outside the App after its adoption. These users should experience the maximum substitution effect, compared to the rest of the users. We should therefore expect a positive and significant interaction coefficient. In all cases, we find that the coefficients on the interactions are economically small and not statistically significant, suggesting there is no evidence of substitution between saving within and outside the App on our data.

5   Why Does Goal-Setting Increase Savings?

The psychology and economics literatures—Locke and Latham (2002, 2006) and Hsiaw (2013); Bénabou and Tirole (2004); Beshears, Milkman, and Schwartzstein (2016)—show the two most important aspects of setting goals rests on the concreteness of the goal and users' ability to monitor their progress. In this section, we show that *monitoring* is the most important channel for the effectiveness of goal setting for saving using three different empirical exercises. First we show that, when surveyed, individuals identify monitoring as the most important channel (Section 5.1). Second, we study how the type of goal and the characteristics of the individual (Section 5.2) relate to saving behavior and show that goals that are easier to monitor (shorter and of lower amount) are achieved more often. Third, we study the main determinants of goal achievement (Section 5.3) and show that the nature of the goal does not matter.

5.1 Survey Evidence

We start with reporting in Panel a) of Figure 8 the distribution of the answers to the question *"In your experience, what is the most motivating aspect of having a saving goal?"* The question emphasized three aspects of goals, that is, the deadline dimension, the ability to track the progress towards the goals, and the nature of the goal. In particular, it gave users the following options: 1) Having a deadline; 2) The nature of the goal; 3) The ability to monitor my progress towards the goal; 4) Other; and 5) I do not think having a goal is motivating.

App users overwhelmingly respond (57%) that the ability to monitor their progress towards the goal was the most motivating aspect, followed by the concreteness of the goal (28.5%) and the having a deadline (10.4%).

We corroborate these results using observational data on individuals' login activity on the App, before and after setting goals. We estimate a regression identical to specification (1), except that we replace the monthly net deposit dependent variable with the (logged) number of monthly logins on the App. We find that individuals increase their login activity on the App by 6% on average, consistent with the intuition that goal setting helps individuals better monitor their progress towards their savings goal.

5.2 Goal-type, User Characteristics and Saving Behavior

In Table 7, we re-estimate the models in Table 2, but condition our estimates on the type of target in Panel A and the user characteristics from our Survey in Panel B. The first column of Table 7 splits the type of targets into four categories: *leisure*, which comprises Hobby and Travel; *durable*, which comprises Car and House; *other*, collecting other specific targets; and *savings*, the generic saving category. We then estimate a regression model:

$$M\_Net\_Deposits_{i,t} = \alpha_i + \alpha_t + \beta\, Target\_Dummy_{i,t} + \sum_{k=1}^{3} \gamma_k\, Target\_Dummy_{i,t} \times Interaction\_k_i + \epsilon_{i,t}$$

where all variables are defined as in Equation (1) and $Interaction\_1_i$ is a dummy equal to 1 if the target falls in the leisure category and zero otherwise, $Interaction\_2_i$ is a dummy equal to 1 if the

target falls in the durable category and zero otherwise and $Interaction\_3_i$ is a dummy equal to 1 if the target falls in the "other" category and zero otherwise. By excluding the generic saving category *savings*, we take it as the base case.

The first column in Panel A of Table 7 shows economically small effects related to the type of target. All interactions are negative but only the ones for "leisure" and "other" are statistically significant. Economically the effects are negative but not very large, suggesting that the specific nature of the target does not have an effect on users' saving behavior, consistent with the survey results.

The second column focuses on the horizon of the goal and $Interaction\_1_i$ identifies targets with horizons of less than (or equal to) a year. We therefore take targets with horizons greater than one year as the base case. Individuals save significantly more when they set targets of short horizon: the coefficient on the short horizon interaction is positive and statistically significant, but the effect is economically small. Combined with the survey findings, these results suggest that the shorter horizon makes it easier for individuals to monitor their progress.

The third column focuses on the amount of the goal and $Interaction\_1_i$ identifies targets smaller than €1,000. We therefore take targets with horizons greater than €1,000 as the base case. We do not find any relation between the size of the target and the saving behavior.

Another dimension we explore is the interaction between the effectiveness of goals and users' traits, which we focus on in Panel B of Table 7. We run the following regression:

$$M\_Net\_Deposits_{i,t} = \alpha_i + \alpha_t + \beta\,Target\_Dummy_{i,t} + \gamma\,Target\_Dummy_{i,t} \times Interaction_i + \epsilon_{i,t}$$

where all regressors are defined as above but now the dummy $Interaction_i$ is equal to one for a subset of the survey respondents on the basis of their levels of financial literacy (column 2), risk aversion (column 3), patience (column 4), education (column 5) and income (column 6).

Ex-ante it is difficult to predict whether users' personality and sophistication increase or decrease the effectiveness of goal-setting. In principle, we expect that risk-aversion and patience to decrease the impact of goal-setting because more patient individuals are less likely to display present biased preferences. The role of financial literacy is also very important, because—from a policy perspective— knowing whether FinTech apps should be deployed in conjunction with financial literacy or in place

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of financial literacy have opposite policy implications.

The first column of Panel B does not include any interaction and simply re-estimates the specification in column 1 of Table 2 on the sample of survey respondents. It establishes that the results on this subsample are very similar to the ones computed on the full sample of App users, allaying concerns of sample selection biases in the population of survey respondents.

In the second column, the dummy $Interaction_i$ is equal to one for those individuals with high financial literacy and zero otherwise. We classify as highly financially literate those individuals who claim to have either medium-high and high knowledge of investing and answer correctly the Lusardi-Mitchell question in the Survey—see Figure A.2 for details. The interaction between financial literacy and goal setting is estimated to increase the effect of goal-setting by 19.82/31.94=62%, which is statistically and economically large.

The third column classifies as highly risk-averse those who answers 1 or 2 (out of 5) to the question of how willing they are to take risks—see Figure A.2 for details. Here we find that risk-averse individuals are significantly less likely to save more after adopting target, possibly because they invest in bond funds with low returns.

The fourth through sixth columns focus on patience, education and income, where high-patience individuals are defined as those who answer €101 or €103 to the patience question, low-education individuals are those who completed high school as their highest level of education and low income individuals are those who earn less than €2,000 in net income per month—see Figure A.2 for details. In no case we find interaction effects that are statistically or economically significant.

Overall, the results in this section suggest that the nature of the target does not have an effect on saving. Among the users' characteristics we observe, financial literacy and risk aversion are the most relevant traits, while patience, education and income do not play a role.

5.3   Likelihood of Achieving Goals

Thus far we have shown that goal-setting has a positive effect on individuals' savings. In this section, we show that users' goals are rarely achieved by investors within the deadline they set. We also show that setting a specific goal, if anything, is negatively related to the probability of obtaining such goal.

We start by presenting basic facts on goal attainment. For this analysis, we restrict the sample to the targets that had a deadline before the date on which we obtained the data, November 2nd, 2019. We have a total of 14,521 goals. Of these 4,088 (28.15%) were attained within the deadline, 3,568 (24.57%) were closed and unattained, and 6,865 (47.28%) were overdue but still active. The closed and overdue goals are generally rather far from being attained. On average, only 11% of the target was funded for closed targets. The corresponding percentage for overdue targets was 13.1%.

To assess whether the specificity of the goal relates to the probability of achieving it, we estimate a logit model of the following form:

$$y_i = \begin{cases} 1 & \text{if goal } i \text{ is achieved} \\ 0 & \text{otherwise,} \end{cases}$$

and

$$p_i = Pr\left(y_i = 1 | \boldsymbol{x}_i\right) = \frac{\exp\left(\boldsymbol{x}_i'\boldsymbol{\beta}\right)}{1 + \exp\left(\boldsymbol{x}_i'\boldsymbol{\beta}\right)}, \tag{5}$$

The vector $\mathbf{x}_i$ contains dummies for the following goals: hobby, travel, other, car, house, and generic savings (the base case). Other control variables included are: the 1) the log transformation of the goal horizon—measured in days; 2) the log amount of the goal; 3) the age of the person setting the goal; and 4) whether a person was a male. All continuous variables are standardized so they have a standard deviation of one.

The results are reported in Table 8. The first and second columns report coefficients for logit models, while columns 3 and 4 provide results for linear probability models. The second and fourth columns include monthly time effects and province fixed-effects. Across all specifications, we find virtually identical results. Starting from goal categories, specific goals are negatively related to the probability of success. The hobby, travel, other, car, and house categories have a probability of success 10 percentage points lower than the generic saving (the base category). As expected, the control variables size and horizon have a large impact on the probability of success. A one standard deviation increase in the size of the goal decreases the probability of success by 13 percentage points, and a one standard deviation increase in the horizon decreases the probability of success by 3 percentage points.

This implies that short-term and small goals are the most likely to be achieved. Also, older users are more likely to achieve their goals, possibly because they are less financially constrained and more responsible with their finances and men are significantly less likely to achieve their goals, possibly because they are overconfident and less responsible than females.

5.3.1 Additional Evidence Provided by the Survey.

Because observational data do not allow us to fully infer what factors determine users' likelihood of achieving their saving goals, we complement these results with survey data. In panel b (c) of Figure 8 we ask users about factors they believe have determined the success (failure) of their goals. Again consistent with Table 8, when asked about their attained goals, only 18% of the users claim the nature of the goal was the most decisive factor. About 54% of respondents claim instead that fund returns and their ability to monitor the progress towards their goal have played a more important role. When asked about the goals they have not attained, a considerable fraction of respondents (27.1%) are unable to provide a precise answer and choose the "Do not know" option. Of the remaining options, the most common is "unexpected expenses" (30%) followed by a too ambitious goal (15.8%), poor fund returns (9%), and lost motivation (7%).

5.3.2 Dynamics of Savings towards the Goal.

The results above are silent on the time-dynamics of saving. For example, do individuals who do not achieve goals get fatigued over time and stop saving as time passes by or do they fail to be on track from the very beginning? For those who achieve their goals, do they save more than they should at the beginning and lose steam as time goes by? Providing answers to these questions is crucial to help individuals design achievable and motivating saving goals.

To this end, we first restrict the sample to the 14,521 goals goals with deadline before the date on which we obtained the data (November 2nd, 2019). To ease the comparison across goals with different characteristics, we normalize to one both the horizon and the amount of each goal. For each goal, we then cumulate the amount deposited by the user over time so that we have the percentage of the goal completed as a function of the percentage of the time elapsed. Finally, we compute semi-parametric

estimates of the average percentage completion across all goals, as a function of the time elapsed.

Results are reported in Figure 9. The first subfigure reports the results pooling across all goals (in black) and separating goals that are attained (in blue), and goals that are unattained (in green).[12] While difficult to discern, the 95% confidence intervals are also reported with dashed lines. We highlight several facts. First, pooling across goals, individuals save only 20% of the goal amount by the time the goal expires, on average. Second, unattained goals are very different from attained ones right from their inception. In the first, individuals under-save from the very beginning—the green line is always below the red 45 degree line—while, if anything, individuals over-save in the first part of the goals that are attained. Individuals over-save up to the 40-th percentile of the time duration of the goal and progressively decrease their saving rate thereafter, only to increase it at the very end to complete the goal.

5.3.3 Alternative Goal Categorization.

The pre-specified categories available on the App might not fully span the nature of the goals set by users. Moreover, after describing the goal, users might be careless in selecting the category to which it belongs to (i.e. she may select the category "savings" even if the name of the target is "Trip to New York"). In both cases, the goal indicator variables in Equation 5 would contain measurement error which, if large enough, could bias the coefficient estimates. To address these concerns, in Online Appendix A we use data from the text entered by the users to describe the goals and re-categorize the goals both manually and using automated machine learning methods. We find that these alternative goal categorizations return the same results.

Overall, the results in this section suggest that the type of goal set by the individuals is barely related to the probability of achieving the target, and that the stronger savings in connection with the adoption of targets documented in the previous section is likely due to the fact that the App allows individuals to monitor and track their progress towards their savings goals.

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[12]Recall that approximately 24.57% of these goals were attained within the deadline.

6   Understanding the Economic Effects of Goal Setting on Saving

In this section, we aim to quantify the economic effects of goal-setting in reducing the under-saving associated with present biased preferences. For these computations, we use the following three quantities. First, individuals' saving rate before adopting goal setting. Second, the implied saving rate associated with saving goals: the saving rate individuals would like to have as they are planning for the future. Third, the saving rate users achieve when they use goal-setting, which is the result of planning and having the freedom to deviate from the original plan.

We interpret the difference between the saving rate implied by goals and the saving rate when not setting a goal as the potential effect of goal setting in increasing savings rate. We interpret the difference between the saving rate implied by the goals and the saving rate obtained with goal-setting as the reduction in saving (leakage) individuals experience because of the freedom associated with soft commitments. Finally, we interpret the difference between the saving rate associated with goals and the saving rate without goals as the realized effect of goal setting in reducing investors' hyperbolic discounting. We display schematically this relation in the diagram reported below:
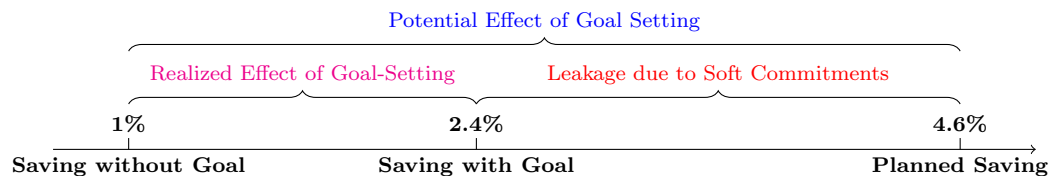
To make our estimates economically meaningful, we focus on the subset of users for which we have income information through the survey. This allows us to compute, for each individual, the saving rate as the percentage of net income associated with each state reported above.[13] As shown in the diagram, the median individual saves 1% of her net income when she does not set goals. The planned percentage savings associated with goals equal 4.6% of her net income. Finally, the percentage savings realized when setting goals equal 2.4% of her income. We obtain virtually identical values when we restrict the analysis to only those individuals who do not save anything outside the App: 1%, 6%, and 2%, respectively.[14] These differences in savings rate highlight two facts. First, there is substantial

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[13]Note that the survey asks users for their net income in discrete intervals—see Figure A.2 for details. We take the mid-point of each interval and assign €4,500 to those who respond they earn more than €4,000.

[14]We work with medians, because they are less affected by outliers. If we use averages we obtain that the average

leakage associated with the soft commitments individuals engage in. Second, goal setting is rather helpful in helping individuals increase their baseline saving rate.

Economically, the effects are rather large. Take an individual who invests in an all equity mutual fund and therefore can expect a 6% annual risk premium. This individual would save one month worth of her net income in 55 months (almost five years). Under the saving rate implied by the saving plan (4.6%) the very same individual would achieve the same overall saving in 19 months (a little less than two years). Finally, if she was engaging in goal-setting, she would achieve that overall saving in 33 months (a little less than 3 years).

7   Conclusions

Present biased and time-inconsistent preferences are often pointed to as the main psychological reasons a large majority of individuals does not save enough to withstand adverse income shocks and is unprepared for retirement. In this paper, we study the effectiveness of *soft, self-designed* commitment devices in saving decisions using data from an App developer that provides its users with simple budgeting solutions in the form of saving goals. We complement the administrative App data with a survey administered on a sample of App users to uncover the economic mechanism underlying individuals' goal-setting choices.

We establish that setting goals increases individuals' saving rate and show that the effect is causal using a difference-in-differences identification strategy that exploits the random assignment of users into a group of beta-testers that can set goals and a group of users that cannot. We also show that the increased savings within the App do not come at the expense of reduced savings outside the App.

We also explore the economics of our findings and show that monitoring is the crucial mechanism underlying the effectiveness of goal-setting for saving, while the nature of the goal or the presence of a deadline are less important. Finally, we show that only a small percentage of the goals (30%) are achieved.

Taken together, our findings indicate that soft, self-designed commitment devices have an overall

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saving rates as percentage of income are 2.1% for individuals who do not set goals and 4.0% for individuals who save with goals—in line with the median values reported in the main body of the paper. The savings rate implied by savings goal plans is instead higher and averages 11.7%, mainly because some individuals set unrealistically high saving goals and the large positive skewness increases the averages.

positive effect on saving. However, individuals oftentimes fail to reach their goals, suggesting there is considerable scope to increase the effectiveness of goal-setting by helping individuals set well-calibrated goals, possibly using robo-advising tools (D'Acunto and Rossi, 2021). In addition, given that mobile phone usage is becoming widespread across developing countries—see Jack and Suri (2014) and Duflo and Banerjee (2011) for examples—the soft, self-designed commitment devices we study in this paper could be deployed to help low income individuals who are arguably the ones who need these FinTech tools the most.

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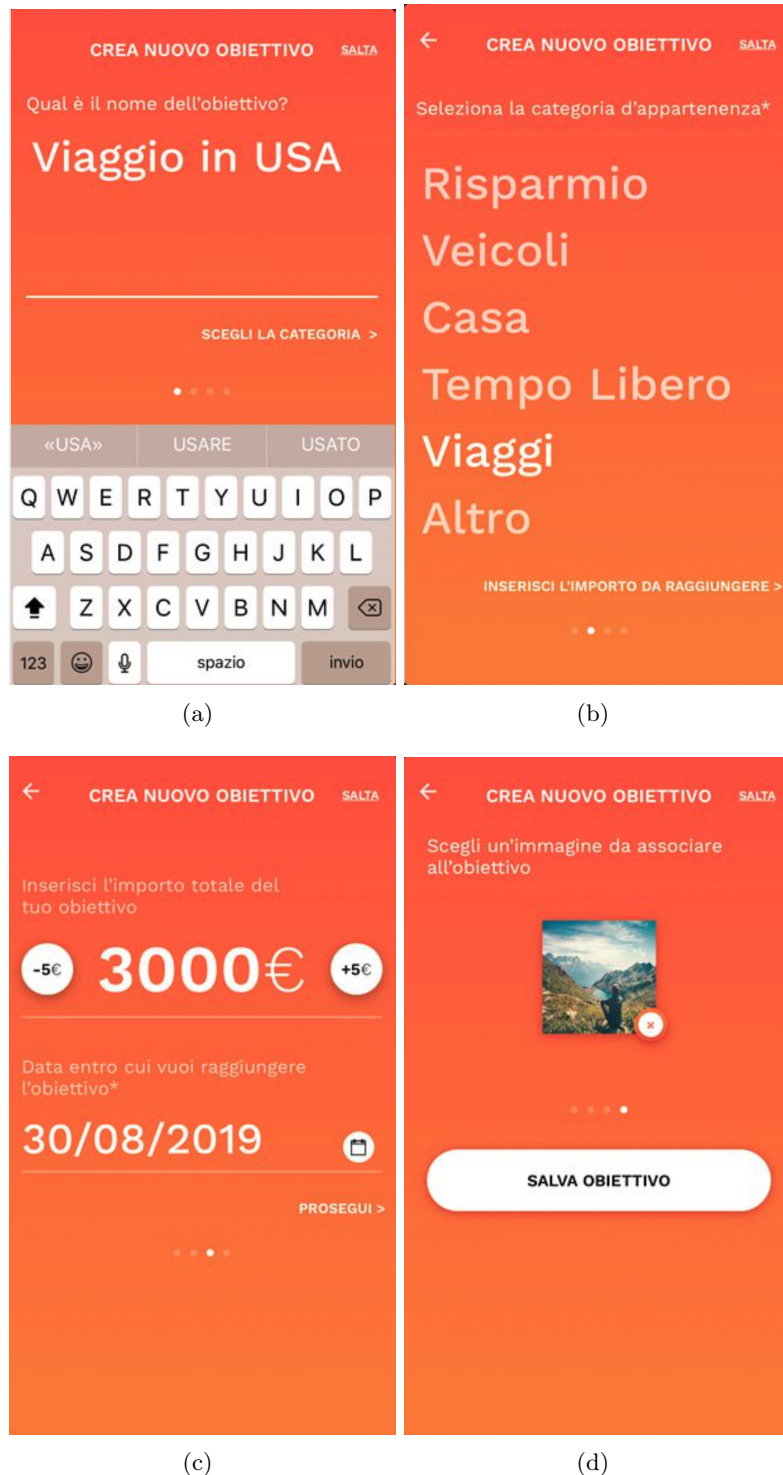
Figure 1: This Figure displays the four steps required to create a saving goal: (a) naming the goal; (b) choosing between six categories: Hobby (Tempo Libero), Travel (Viaggi), Other (Altro), Car (Veicoli), House (Casa) and Savings (Risparmio); (c) choosing a target amount (e.g. € 3000) and a deadline (e.g. 30/08/2019); (d) Linking the goal to an image.
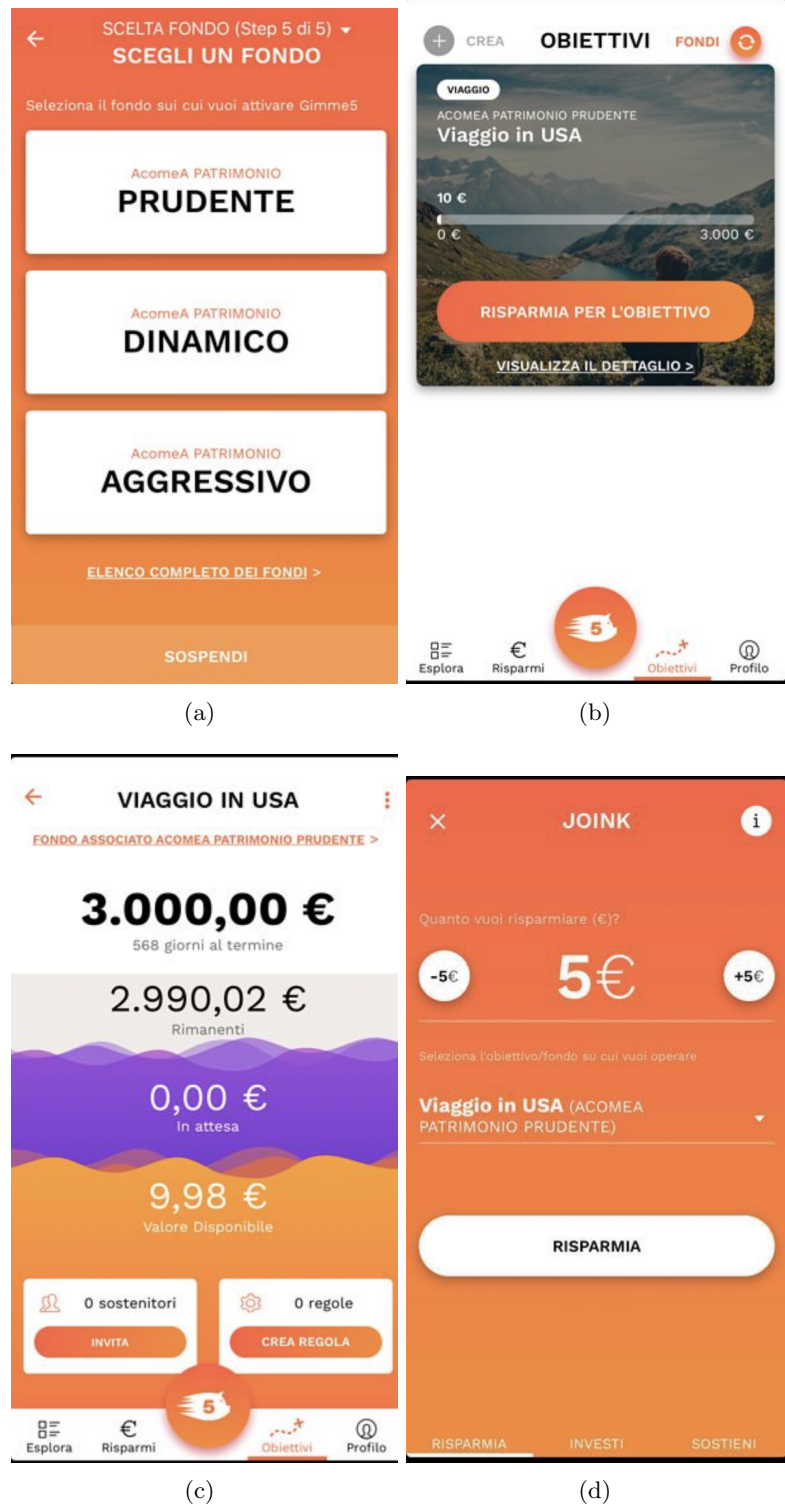
Figure 2: This Figure displays the section of the App where users choose the mutual fund for their savings (a); monitor the goal progression (b and c); pledge money with the "Joink" function (d).
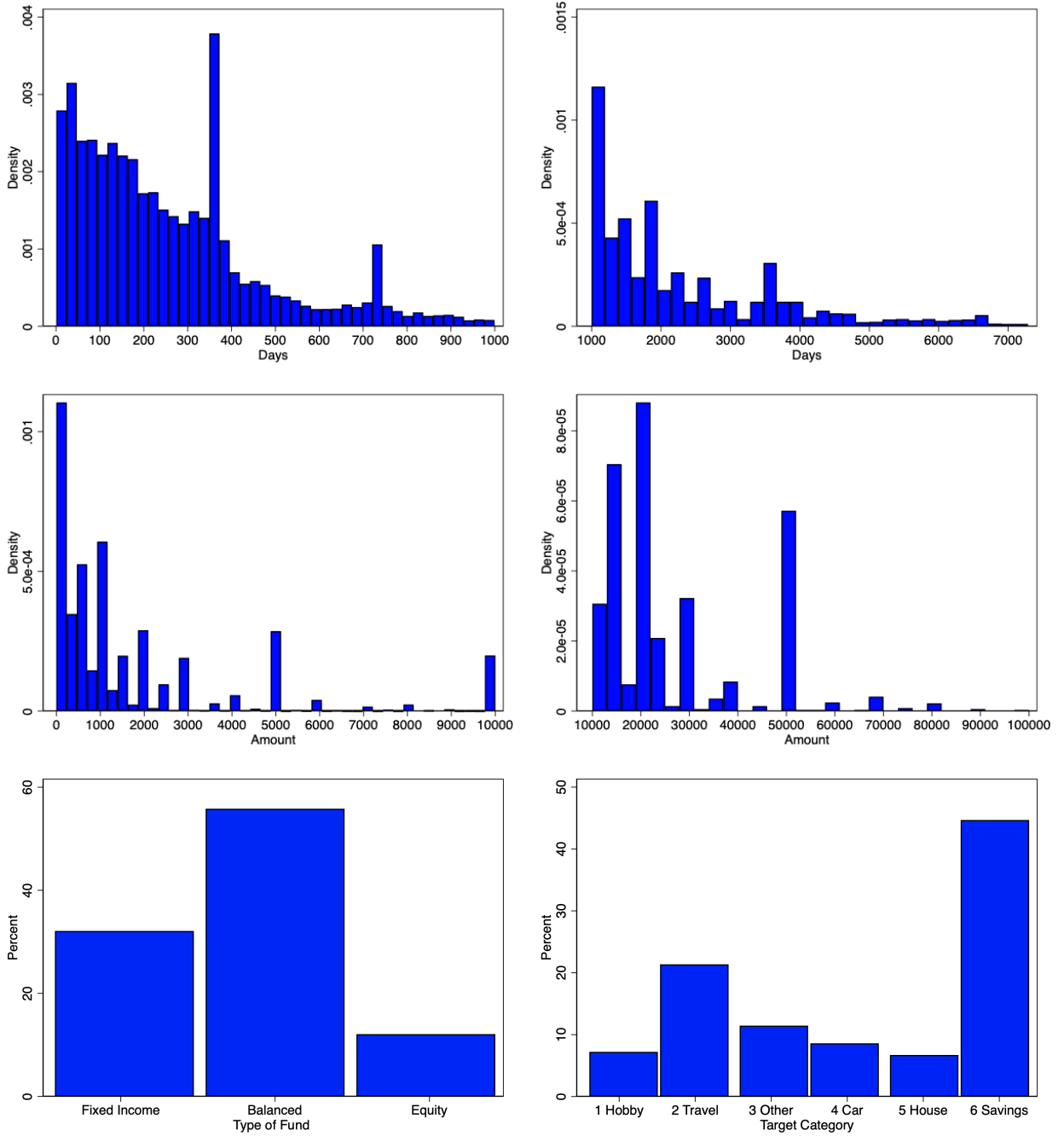
Figure 3: This figure displays the cross-sectional distribution of four key features of the saving goals set by users. The upper subfigures report the horizon of each goal, computed as the difference (in days) between the targeted day and the day when the goal was set. Because the distribution displays a thin right tail, we display it in two parts: the upper-left subfigure is associated with horizons shorter than 1,000 days while the upper-right one is associated with horizons longer than 1,000 days. The middle subfigures report the amounts (in €) users set to save. The left subfigure refers to goals less than or equal to €10,000, while the right subfigure refers to goals grater than €10,000. The bottom-left subfigure displays the type of funds users invest their savings in: Fixed Income, Balanced and Equity funds. The bottom-right subfigure displays the categories of goals users can choose from: Hobby, Travel, Other, Car, House and Savings.
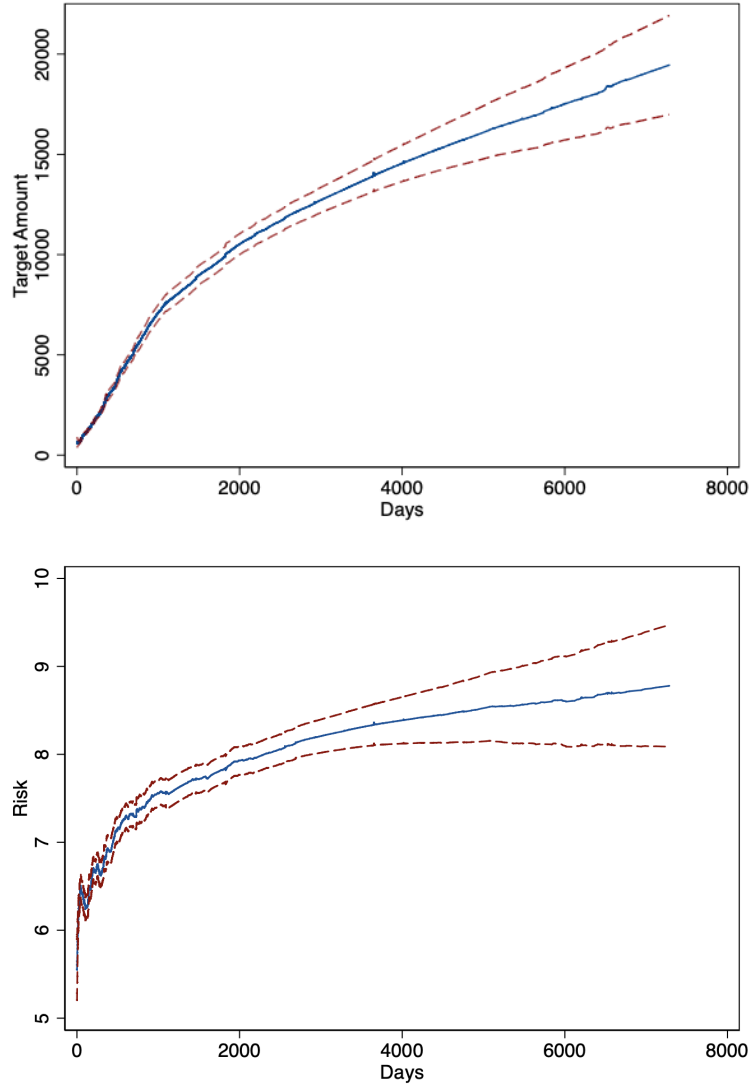
Figure 4: This figure displays the relation between the goal amount (upper subfigure), risk (bottom subfigure), and horizon. The blue lines denote the nearest neighbor estimate of the conditional mean, while the red dashed lines denote the 95% confidence intervals. Risk is measured as the annualized volatility of the fund.
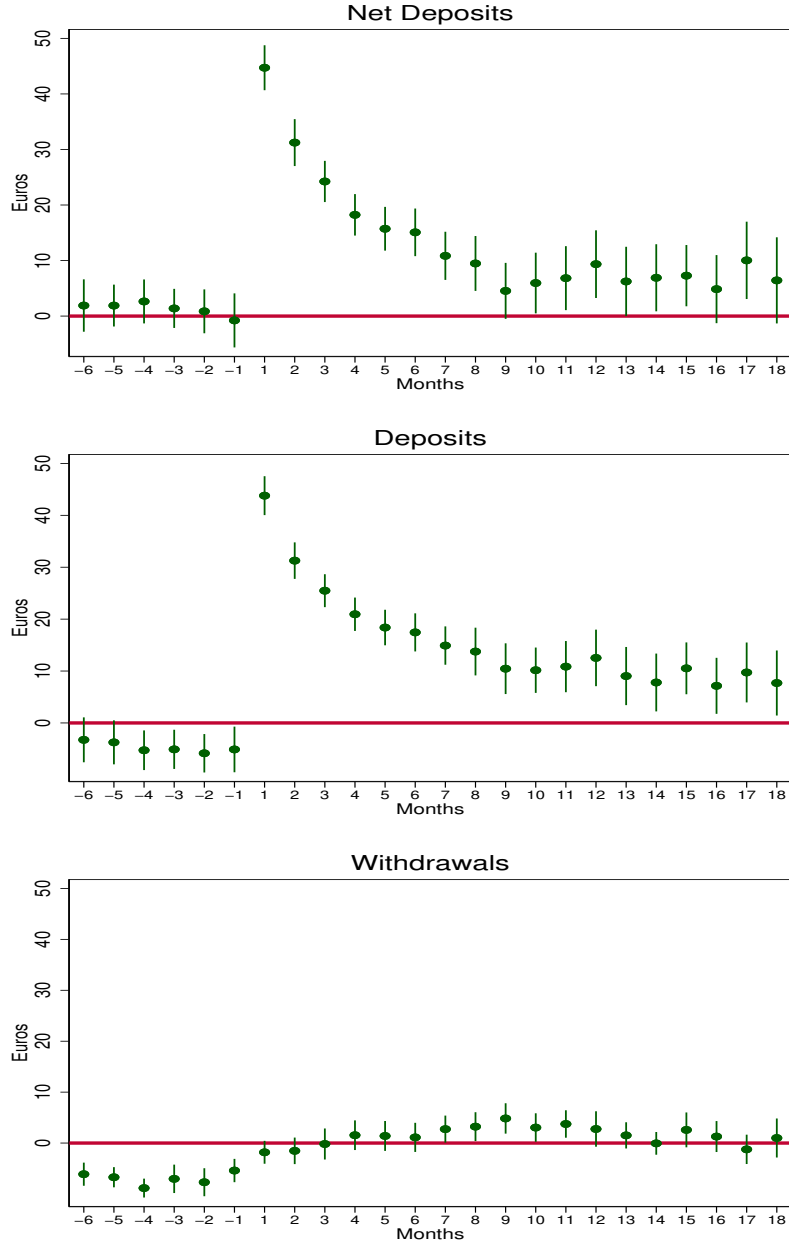
Figure 5: This figure reports coefficient estimates and 95% confidence interval of the β_s coefficients from the following baseline panel regression:

$$M\_Net\_Deposits_{i,j,t} = \alpha_i + \alpha_t + \sum_{s=-6}^{18} \beta_s\ Target\_Dummy_{i,j,s,t} + \epsilon_{i,j,t}.$$

where $M\_Net\_Deposits_{i,j,t}$ denotes the monthly amount (in €) transacted by user i in account j at time t; α_i and α_t identify user and time fixed-effects; $Target\_Dummy_{i,j,s,t}$ is a dummy variable equal to 1 if account j associated with user i is using a target for the $s - th$ month in the calendar month t. The sample is restricted to the individual-account-time triplets where a given user had at least one account where goal-setting was taking place and at least one account where goal-setting was not taking place. The result in the upper subfigure are based on $Net\ Deposits$, i.e. the difference between total monthly $Deposits$ and $Withdrawals$, while the results in the second and bottom subfigures only use $Deposits$ and $Withdrawals$, respectively. The standard errors are double-clustered at the user and month levels.

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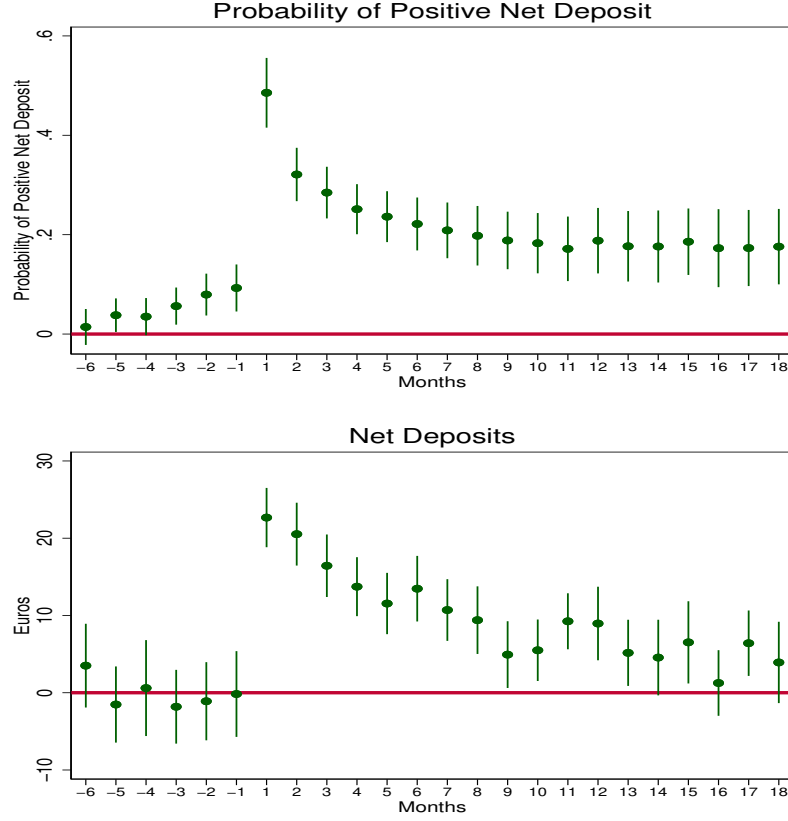
Figure 6: This figure reports coefficient estimates and 95% confidence interval of the β_s coefficients from the following regressions:

$$IND_{i,j,t} = \alpha_i + \alpha_t + \sum_{s=-6}^{18} \beta_s \, Target\_Dummy_{i,j,s,t} + \epsilon_{i,j,t} \qquad (Top \ Subfigure)$$

$$M\_Net\_Deposits_{i,j,t}^{+} = \alpha_i + \alpha_t + \sum_{s=-6}^{18} \beta_s \, Target\_Dummy_{i,j,s,t} + \epsilon_{i,j,t} \qquad (Bottom \ Subfigure)$$

where $IND_{i,j,t}$ is an indicator variable equal to 1 if user i deposited a positive amount in account j in month t and 0 otherwise and $M\_Net\_Deposits_{i,j,t}^{+}$ denotes the monthly net deposit (in €) by user i in account j at time t, conditional on $IND_{i,j,t}$ being equal to 1; α_i and α_t identify user and time fixed-effects; $Target\_Dummy_{i,j,s,t}$ is a dummy variable equal to 1 if account j associated with user i is using a target for the $s - th$ month in the calendar month t. The standard errors are double-clustered at the user and month levels.
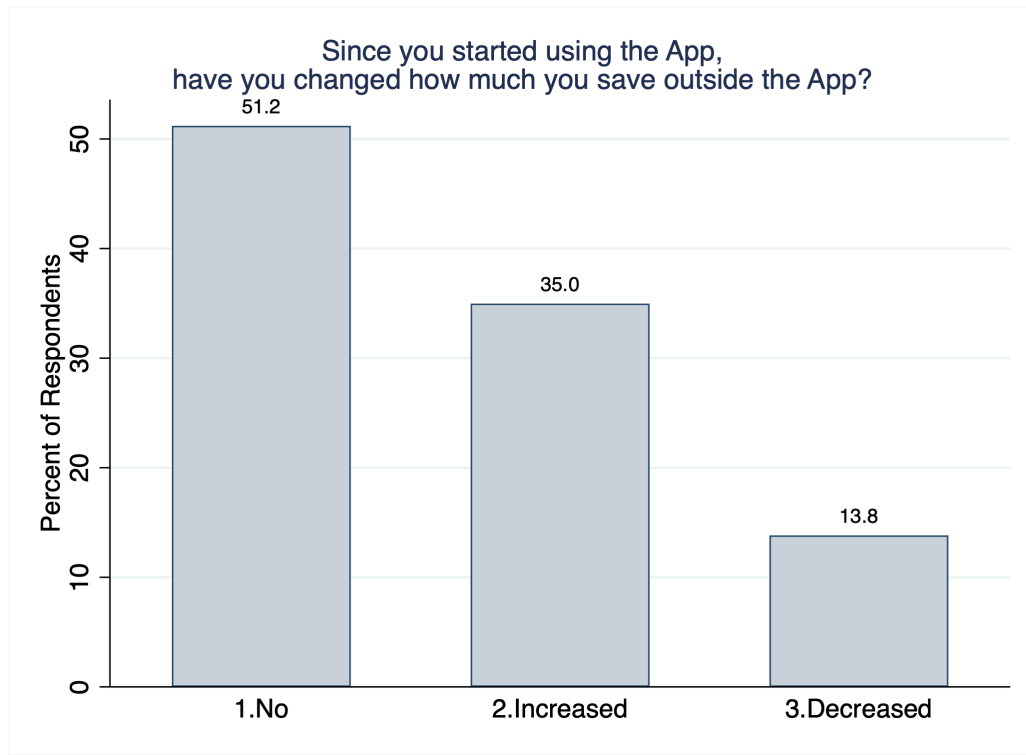
(a)
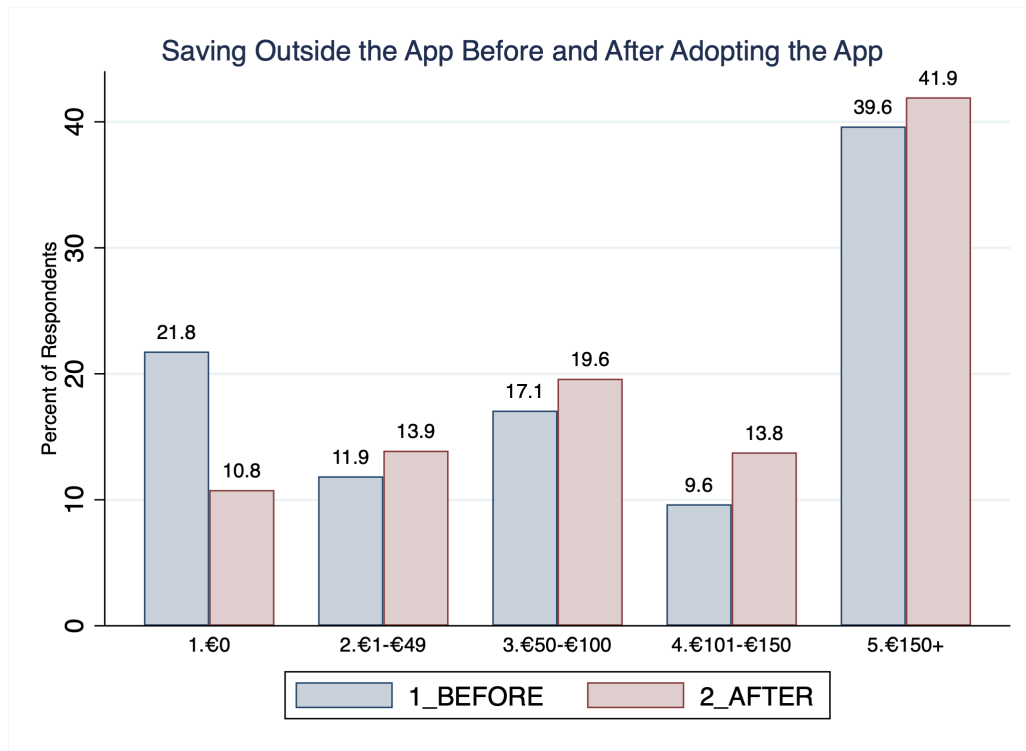
(b)

Figure 7: This Figure shows the distribution of the answers to the survey questions relative to users' saving behavior outside the App before and after its adoption. The question associated with Panel a) is *"Since using the App, have you changed how much you saved outside the App?"*. The questions associated with Panel b) are *"Before using the App, how much have you saved on average per month outside the App?"* (blue bars) and *"Since using the App, how much have you saved on average per month outside the App?"* (red bars). We display the percentage of respondents at the top of each bar.
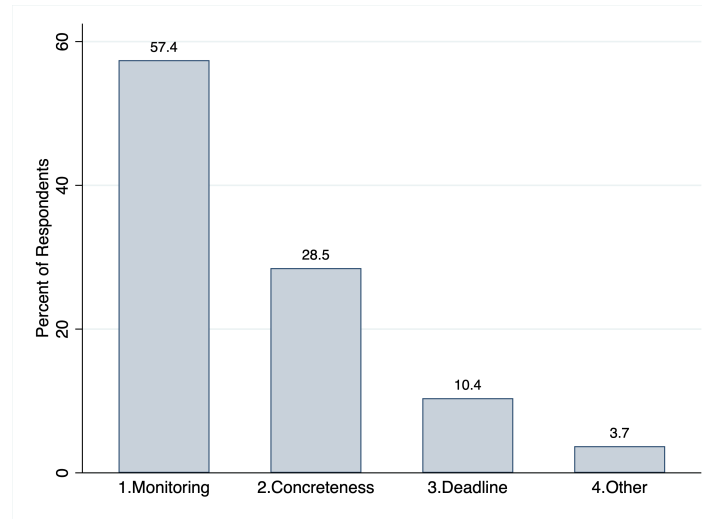
(a) Motivating Aspects of Saving Goals
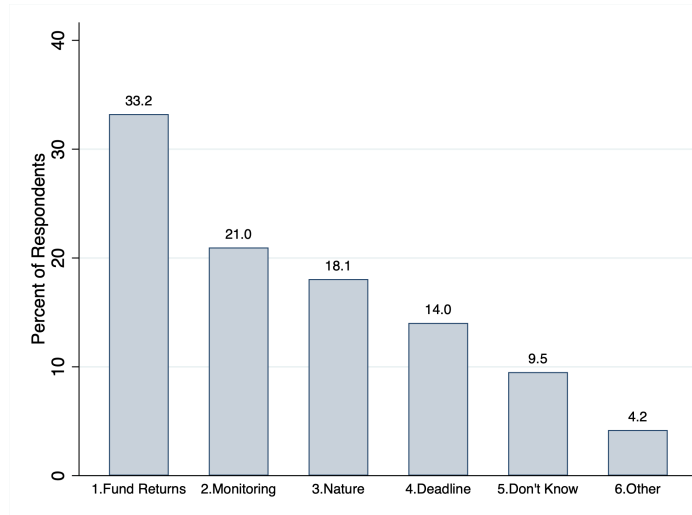
(b) Attained Goals
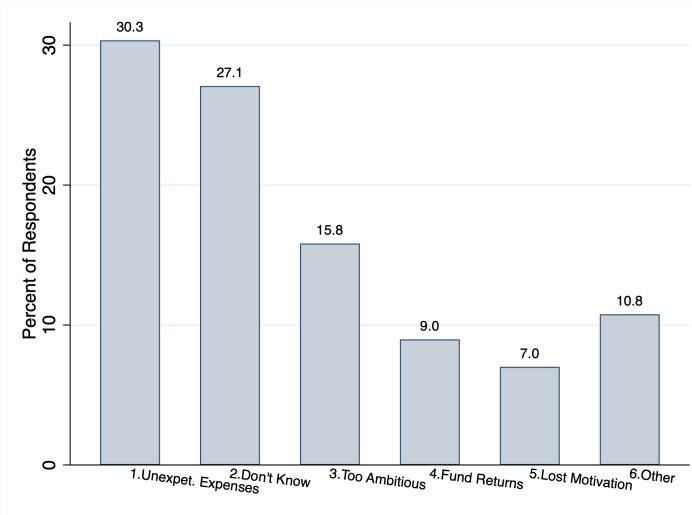
(c) Not Attained Goals

Figure 8: This Figure shows the distribution of the answers to the survey questions relative to the use of saving goals. The question associated with Panel a) is *"In your experience, what is the most motivating aspect of having a saving goal?"*. The question associated with Panel b) is *"Think about the saving goals you have achieved. In your opinion, what has been the most decisive factor?"*. The question associated with Panel c) is *"Think about the saving goals you have NOT achieved. In your opinion, what has been the most decisive factor?"*. We display the percentage of respondents at the top of each bar.
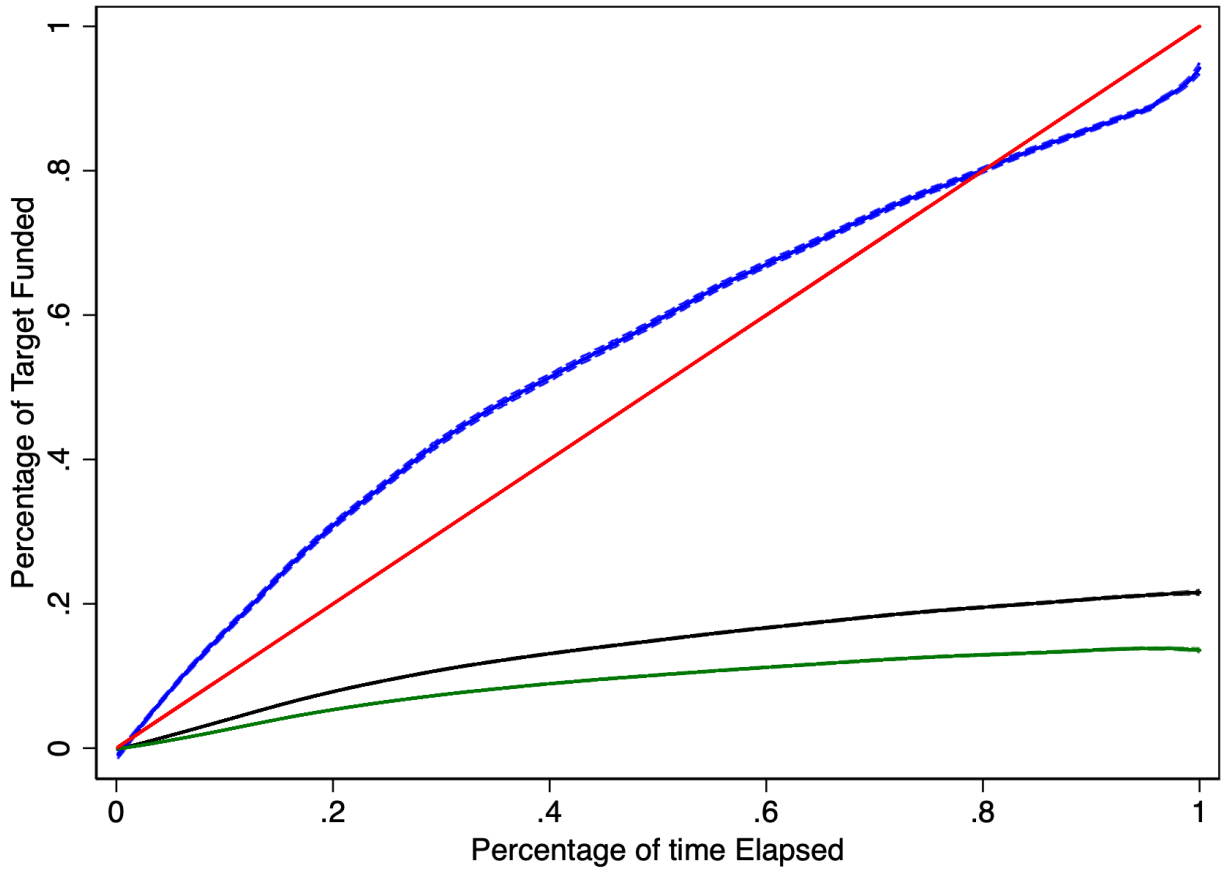
Figure 9: This figure analyzes the dynamics of saving when individuals set goals. The sample consists of the 14,521 goals with deadline before the date on which we obtained the data (November 2nd, 2019). To ease the comparison across goals with different characteristics, we normalize to one both the horizon and the amount of each goal. For each goal, we then cumulate the amount deposited by the user over time so that we have the percentage of the goal completed as a function of the percentage of the time elapsed. Finally, we compute semi-parametric estimates of the average percentage completion across all goals, as a function of the time elapsed. The black line refers to all goals, the blue line to attained goals and the green line to unattained loans.

Table 1. Summary Statistics

Panel A. Demographic Characteristics

	N	mean	sd	p1	p25	p50	p75	p99
Male	47,643	0.81	0.39	0.00	1.00	1.00	1.00	1.00
Age	47,216	36.46	11.82	19.00	27.00	35.00	44.00	68.00

Panel B. App Usage by Users

	N	mean	sd	p1	p25	p50	p75	p99
Tenure	27,439	11.48	14.02	1.00	1.00	5.33	16.73	59.27
N. Transactions per Month	27,439	1.14	0.94	0.08	0.57	1.00	1.41	4.23
Size of Net Deposit	27,439	35.35	29.96	0.33	20.19	29.28	43.93	141.71
Net Deposit per Month	27,439	35.04	96.19	-1.84	0.18	5.01	30.00	463.34

Panel C. Accounts and Targets

	N	mean	sd	p1	p25	p50	p75	p99
N. of Savings Accounts	47,746	1.11	0.49	1.00	1.00	1.00	1.00	4.00
Target Present	47,746	0.27	0.44	0.00	0.00	0.00	1.00	1.00
N. Targets	17,240	1.43	1.32	1.00	1.00	1.00	1.00	6.00
N. Active Targets	17,240	0.86	0.67	0.00	1.00	1.00	1.00	4.00
N. Closed Targets	17,240	0.29	0.69	0.00	0.00	0.00	0.00	3.00
N. Won Targets	17,240	0.28	0.97	0.00	0.00	0.00	0.00	4.00

This Table reports cross-sectional summary statistics for the users in our sample. We first compute the value of each variable at the user level and then report the distribution of the variable across all users. For each variable, we report the number of observations used in the second step of the computations, the mean and standard deviation of each variable, as well as the $1st$, $25th$, $50th$, $75th$, and $99th$ percentile. Panel A refers to the demographic characteristics: *Male* (1 for males and 0 for females) and *Age* (as of November 2019). Panel B refers to the App usage. The variables in this panel are based only on the individuals that have transacted at least once on the platform. *Tenure* denotes the number of months between the first and the last transaction we observe; $N.\ Transactions\ per\ Month$, denotes the average number of transactions per month (computed as the ratio between the total number of transactions over the full sample and *Tenure*); *Size of Net Deposit*, is the difference between total Deposits and Total Withdrawals made by the user over her *Tenure*; *Net Deposit per Month* is the average monthly difference between total Deposits and Total Withdrawals made by the user over her *Tenure*. Panel C refers to facts regarding the number of accounts and targets associated with each user. *N. of Savings Accounts* is the total number of savings accounts opened by a given user; *Target Present* is the number of accounts per user associated with a target; *N. Targets* is the number of targets; *N. Active Targets*, *N. Closed Targets*, *N. Won Targets* are the number of Active (as of November 2019), Closed and Achieved targets, respectively.

Table 2. Effect of Goal-Setting on Saving Behavior:
Baseline Results at the User Level

	(1) Net Deposits	(2) Deposits	(3) Withdrawals
Target Dummy	28.74***	34.56***	5.60***
	(16.37)	(20.24)	(5.67)
Constant	31.61***	41.06***	10.15***
	(69.53)	(92.58)	(39.76)
R-Squared	0.34	0.44	0.18
Obs	307,501	307,501	307,501

This table reports coefficient estimates and associated t-statistics (in parentheses) of the following panel regression:

$$Transaction_{i,t} = \alpha_i + \alpha_t + \beta \ Target\_Dummy_{i,t} + \epsilon_{i,t}$$

where $Transaction_{i,t}$ denotes the monthly amount (in €) transacted by individual i during month t; α_i and α_t identify user and time fixed-effects; $Target\_Dummy$ is an indicator variable equal to "0" if the user has no goals in her account at time t, and equal to "1" if she set at least one goal at time t. The result in the first column are based on $Net \ Deposits$, i.e. the difference between total $Deposits$ and $Withdrawals$, while the results in columns (2) and (3) only use $Deposits$ and $Withdrawals$, respectively. The standard errors are double-clustered at the user and month levels. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 3. Effect of Goal-Setting
on Saving Behavior at the Account Level

Panel A. All Individuals

	(1) Net Deposits	(2) Deposits	(3) Withdrawals
Target Dummy	26.84***	29.40***	1.61
	(18.31)	(19.57)	(1.61)
Constant	27.17***	36.20***	9.87***
	(67.73)	(87.40)	(35.88)
R-Squared	0.29	0.39	0.16
Obs	347,411	347,411	347,411

Panel B. Only Individuals who Save
With and Without Targets

	(1) Net Deposits	(2) Deposits	(3) Withdrawals
Target Dummy	54.85***	55.87***	-0.26
	(18.51)	(17.76)	(-0.21)
Constant	17.32***	26.67***	10.60***
	(11.70)	(16.79)	(18.97)
R-Squared	0.31	0.40	0.21
Obs	30,774	30,774	30,774

This table reports coefficient estimates and associated t-statistics (in parentheses) of the following panel regression:

$$Transaction_{i,j,t} = \alpha_i + \alpha_t + \beta \ Target\_Dummy_{i,j,t} + \epsilon_{i,j,t}$$

where $Transaction_{i,j,t}$ denotes the monthly amount (in €) transacted by user i in account j at time t; α_i and α_t identify user and time fixed-effects; $Target\_Dummy_{i,j,t}$ is a dummy variable equal to 1 if account j associated with user i at time t is characterized by goal-setting, and zero otherwise. Panel A is based on all the individual- account-time triplets to estimate coefficients, while Panel B only uses those individual-account-time triplets where a given user had at least one account where goal-setting was taking place and at least one account where goal-setting was not taking place. The results in the first column are based on *Net Deposits*, i.e. the difference between total *Deposits* and *Withdrawals*, while the results in column (2) and (3) only use *Deposits* and *Withdrawals*, respectively. The standard errors are double-clustered at the user and month levels. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 4. Identification Strategy I.
Results at the Account Level

Panel A. All Individuals

	(1) Net Deposits	(2) Deposits	(3) Withdrawals
Treated Dummy	5.22***	5.41***	0.68***
	(3.40)	(3.73)	(3.28)
Constant	32.10***	34.60***	1.64***
	(98.32)	(86.47)	(61.91)
R-Squared	0.41	0.43	0.20
Obs	347,411	347,411	347,411

Panel B. Only Individuals who Save
With and Without Targets

	(1) Net Deposits	(2) Deposits	(3) Withdrawals
Treated Dummy	3.67**	2.22	0.98***
	(2.18)	(1.27)	(4.41)
Constant	39.76***	43.09***	1.97***
	(20.75)	(31.38)	(14.40)
R-Squared	0.39	0.41	0.19
Obs	159,781	159,781	159,781

This table reports coefficient estimates and associated t-statistics (in parentheses) of the following differences-in-differences model:

$$Transaction_{i,j,t} = \alpha_i + \alpha_t + \beta \ Treated_{i,t} + \epsilon_{i,j,t},$$

where $Transaction_{i,j,t}$ denotes the monthly amount (in €) transacted by user i in account j at time t; α_i and α_t identify user and time fixed-effects; $Treated_{i,t}$ that is equal to 1 for the 122 beta testers for the 50 days (from August 1, 2017 to September 20, 2017) over which they had access to the goal-setting features of the App while the rest of the App users did not. Panel A uses all the individual-account-time triplets to estimate coefficients while Panel B only uses those individual-account-time triplets where a given user had at least one account where goal-setting was taking place and at least one account where goal-setting was not taking place. The results in the first column are based on *Net Deposits*, i.e. the difference between total *Deposits* and *Withdrawals*, while the results in column (2) and (3) only use *Deposits* and *Withdrawals*, respectively. The standard errors are double-clustered at the user and month levels. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 5 Statistics of Matched Sample

Panel A: Beta Testers

	Mean	Std	p5	p25	p50	p75	p95
Tenure	564.11	303.24	206.00	366.00	466.00	717.00	1,192.00
N. Accounts	1.02	0.14	1.00	1.00	1.00	1.00	1.00
Net Inflow	209.67	289.14	6.03	34.57	70.08	267.49	773.38
Risk	8.63	3.58	3.25	6.19	7.55	11.12	16.36
Male	0.86	0.35	0.00	1.00	1.00	1.00	1.00
Age	40.91	9.42	27.00	33.00	41.00	47.00	58.00

Panel B: Other Users

	t-test	Mean	Std	p5	p25	p50	p75	p95
Tenure	-4.29	436.67	333.05	24.00	178.00	357.00	641.00	1,142.00
N. Accounts	-1.20	1.00	0.07	1.00	1.00	1.00	1.00	1.00
Net Inflow	-2.95	126.18	262.08	1.00	5.00	25.00	100.52	673.15
Risk	-1.69	8.04	3.34	2.22	6.19	7.55	9.45	15.40
Male	-1.33	0.81	0.39	0.00	1.00	1.00	1.00	1.00
Age	-0.24	40.68	11.47	24.00	32.00	40.00	48.00	61.00

Panel C: Matched Users

	t-test	Mean	Std	p5	p25	p50	p75	p95
Tenure	0.63	592.92	352.19	106.00	291.00	528.00	891.00	1,262.00
N. Accounts	-1.42	1.00	0.00	1.00	1.00	1.00	1.00	1.00
Net Inflow	-1.14	166.12	262.77	1.00	1.62	45.50	242.91	659.00
Risk	-0.06	8.60	3.97	2.22	6.19	7.55	9.66	16.36
Male	0.32	0.87	0.33	0.00	1.00	1.00	1.00	1.00
Age	0.12	41.08	10.54	26.00	33.00	40.00	48.00	59.00

This Table presents cross-sectional summary statistics for the sample of beta testers (Panel A), the rest of the users (Panel B) and the matched users (Panel C). We first compute the value of each variable at the user level and then report the distribution of the variable across all users. We report the mean and standard deviation of each variable, as well as the 5th, 25th, 50th, and 75th, and 95th percentile. *Tenure* is the number of months elapsed from the opening of user's first account to July 2017—the beginning of the beta-testing period; *N. Accounts*, is the number of accounts opened from January 2017 to July 2017; *Net Inflow* is the monthly average net deposit into the App from January 2017 to July 2017; *Risk*, is the average annual standard deviation across the mutual funds used by the user; *Gender*, is a dummy variable equal to one if male; and *Age* is age measured as of July 2017. In Panels B and C we also report the *t*-stat associated with tests on the equality of means between beta-testers and non-beta-testers along the various characteristics. To create the sample of users in Panel C, we use a nearest neighbor propensity score matching procedure whereby each beta-tester is matched to a single user on the App.

Table 6. Identification Strategy II.
Results at the Account Level with Matching

Panel A. All Individuals

	(1) Net Deposits	(2) Deposits	(3) Withdrawals
Treated Dummy	11.47***	11.75***	3.07***
	(5.81)	(5.80)	(4.48)
Constant	46.42***	52.37***	5.13***
	(20411)	(36215)	(1904)
R-Squared	0.39	0.43	0.23
Obs	8,297	8,297	8,297

Panel B. Only Individuals who Save
With and Without Targets

	(1) Net Deposits	(2) Deposits	(3) Withdrawals
Treated Dummy	14.80***	14.70***	4.19***
	(4.71)	(4.93)	(7.02)
Constant	46.42***	51.40***	4.84***
	(41444.15)	(15940.14)	(1299.46)
R-Squared	0.27	0.29	0.11
Obs	4,400	4,400	4,400

This table reports coefficient estimates and associated t-statistics (in parentheses) of the following differences-in-differences model:

$$Transaction_{i,j,t} = \alpha_i + \alpha_t + \beta\ Treated_{i,t} + \epsilon_{i,j,t},$$

where $Transaction_{i,j,t}$ denotes the monthly amount (in €) transacted by user i in account j at time t; α_i and α_t identify user and time fixed-effects; $Treated_{i,t}$ that is equal to 1 for the 122 beta testers for the 50 days (from August 1, 2017 to September 20, 2017) over which they had access to the goal-setting features of the App. The control group comprises non-beta testers matched to the characteristics of the beta-testers according to the following characteristics computed from January to July 2017: *Male*, the sex of the user; *Age*; *Account Num*, the number of accounts associated with each user; *Net Inflow*, the monthly net deposits into the account; *tenure*, the number of months the user has used the app as July 2017; and *Risk*, the average risk of the funds selected by the user. The results focus on nearest neighbor matches that associate each beta-tester to a single user on the App. Panel A uses all the individual-account-time triplets to estimate coefficients while Panel B only uses those individual-account-time triplets where a given user had at least one account where goal-setting was taking place and at least one account where goal-setting was not taking place. The results in the first column are based on *Net Deposits*, i.e. the difference between total *Deposits* and *Withdrawals*, while the results in column (2) and (3) only use *Deposits* and *Withdrawals*, respectively. The standard errors are double-clustered at the user and month levels. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 7. The Effect of Goal and User Characteristics on Saving Behavior

Panel A. Heterogeneity in Target Characteristics

	Target Type	Target Horizon	Target Size
Target Dummy×Interaction_1	-4.57**	6.02***	-2.01
	(-2.63)	(3.21)	(-1.13)
Target Dummy×Interaction_2	-3.05		
	(-1.06)		
Target Dummy×Interaction_3	-8.52***		
	(-3.53)		
Target Dummy	29.68***	23.56***	27.90***
	(17.90)	(12.18)	(13.18)
Constant	27.15***	27.30***	27.14***
	(68.78)	(68.22)	(64.78)
R-Squared	0.29	0.29	0.29
Obs	347,331	347,411	347,411

Panel B. Heterogeneity in User Characteristics

	Financial Literacy	Risk Aversion	Patience	Education	Income
Target Dummy×Interaction		19.82**	-23.44*	2.38	-6.67	-1.16
		(2.27)	(-1.80)	(0.22)	(-0.74)	(-0.13)
Target Dummy	33.98***	31.94***	38.23***	34.60***	40.21***	35.85***
	(7.45)	(6.24)	(8.10)	(7.55)	(5.33)	(5.05)
Constant	44.62***	43.96***	42.33***	43.64***	42.47***	43.60***
	(21.67)	(20.66)	(20.70)	(21.35)	(21.47)	(20.83)
R-Squared	0.34	0.33	0.33	0.33	0.33	0.33
Obs	19,279	17,698	17,574	17,698	17,577	17,698

This table reports, in Panel A, coefficient estimates and associated t-statistics (in parentheses) of the following panel regression:

$$M\_Net\_Deposits_{i,t} = \alpha_i + \alpha_t + \beta \, Target\_Dummy_{i,t} + \sum_{k=1}^{3} \gamma_k \, Target\_Dummy_{i,t} \times Interaction\_k_i + \epsilon_{i,t}$$

where $M\_Net\_Deposits_{i,t}$ denotes the monthly net amount (in €) deposited by user i at time t; α_i and α_t identify user and time fixed-effects; $Target\_Dummy_{i,t}$ is a dummy variable equal to 1 if user i at time t has a target and $Interaction\_1_i$ is a dummy equal to 1 if the target falls in the leisure category and zero otherwise, $Interaction\_2_i$ is a dummy equal to 1 if the target falls in the durable category and zero otherwise and $Interaction\_3_i$ is a dummy equal to 1 if the target falls in the "other" category and zero otherwise. In the second column, $Interaction\_1_i$ identifies targets with horizons of less than (or equal to) a year and in the third column $Interaction\_1_i$ identifies targets smaller than €1,000. Panel B focuses on the characteristics of the users. We run the following regression:

$$M\_Net\_Deposits_{i,t} = \alpha_i + \alpha_t + \beta \, Target\_Dummy_{i,t} + \gamma \, Target\_Dummy_{i,t} \times Interaction_i + \epsilon_{i,t}$$

where all regressors are defined as above. The first column of Panel B does not include any interaction and simply re-estimates the specification in column 1 of Table 2 on the sample of survey respondents. Columns two through six focus on financial literacy, risk-aversion, patience education and income, respectively. Please refer to Section 5.2 for their definition. The standard errors are double-clustered at the user and month levels. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 8. Determinants of Goal Achievement

	Spec 1	Spec 2	Spec 3	Spec 4
Hobby	-0.54***	-0.56***	-0.11***	-0.11***
	(-7.12)	(-7.13)	(-7.75)	(-7.73)
Travel	-0.75***	-0.73***	-0.13***	-0.13***
	(-13.26)	(-12.68)	(-14.98)	(-14.30)
Other	-0.53***	-0.50***	-0.10***	-0.09***
	(-8.00)	(-7.26)	(-8.73)	(-7.98)
Car	-0.83***	-0.82***	-0.12***	-0.11***
	(-8.60)	(-8.27)	(-9.70)	(-9.07)
House	-0.62***	-0.63***	-0.11***	-0.11***
	(-6.56)	(-6.52)	(-7.27)	(-7.35)
Target Size	-0.68***	-0.72***	-0.13***	-0.13***
	(-28.01)	(-28.31)	(-28.60)	(-28.80)
Horizon	-0.11***	-0.17***	-0.02***	-0.03***
	(-4.72)	(-6.90)	(-5.03)	(-7.05)
Male	-0.45***	-0.47***	-0.07***	-0.08***
	(-7.62)	(-7.81)	(-8.15)	(-8.55)
Age	0.47***	0.45***	0.09***	0.08***
	(22.74)	(20.73)	(23.42)	(21.08)
Constant	-0.61***	-4.72***	0.37***	0.11
	(-20.37)	(-3.68)	(61.24)	(0.81)
Time FE	✗	✓	✗	✓
Province FE	✗	✓	✗	✓
R-Squared	0.13	0.16	0.14	0.18
Obs	13,838	13,823	13,838	13,838

This table reports coefficient estimates and associated t-statistics (in parentheses) of the following regression:

$$p_i = Pr\left(y_i = 1 | \boldsymbol{x}_i\right) = \frac{\exp\left(\boldsymbol{x}_i'\boldsymbol{\beta}\right)}{1 + \exp\left(\boldsymbol{x}_i'\boldsymbol{\beta}\right)},$$

where the dependent variable is 1 if goal i is achieved and 0 otherwise. The vector $\mathbf{x}_i$ includes dummies for the following categories of goals: hobby, travel, car, house, and generic savings (the base case), and controls including the log transformation of the goal horizon, measured in days; the log transformation of the goal amount; the age of the user; a male dummy; monthly and province fixed-effects. The first and second (third and fourth) columns report coefficients for logit (linear probability) models. The second and fourth column include monthly time effects and province fixed-effects. All the continuous variables have been standardized so that they have a standard deviation of one. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Online Appendix to
Correcting Present Bias in Saving Decisions with FinTech

Antonio Gargano

University of Houston

Alberto G Rossi

Georgetown University

(Not for publication)

Appendix A Likelihood of Achieving Goals: Alternative Categorization of Goals

We use data from the text entered by the users to describe the goals and manually re-categorize the goals using both a fine and a coarse scheme. The fine categorization includes *Travel*, *Vehicle*, *House*, *Celebrations*, *Family*, *Hobby*, *Consumer Goods*, *Health*, *Liability*, *Entrepreneurship*, *Saving* and *Other*.[15] The coarse categorization matches the one available on the App.[16] We also use a machine learning technique, the Latent Dirichlet Allocation (LDA), to create topics and assign targets to them. Consistent with the manual classification, we impose a fine scheme (which includes 11 topics in addition to the general *Savings* category) and a coarse scheme (which includes 5 topics in addition to the general *Savings* category). The advantage of this approach is that the resulting categorization does not involve human judgement.

We then re-estimate the linear probability model in Equation (5) using dummies based on both categorizations and keeping *Savings* as our base case. If selecting a more specific goal improves the achievement rate but the pre-specified categories available on the App do not fully span the nature of the goals set by the users, we would expect at least one of the finer categories to be associated with a positive coefficient. Similarly, if the users did not pay attention when selecting the goal category, we should find results different from Table 8 using the coarser manual categorization. We present the results in Table A.5, where columns 1 and 2 report the results for the fine and coarse manual classification, while columns 3 and 4 report the results for the machine learning classification.

Starting from the manual categorization, we find again that specific goals are negatively related to the probability of success. Relative to the category used as base (general *Savings*), the targets in the fine categories have a lower probability of being achieved. The *Health* category displays the largest

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[15]The *Holiday* goal includes words like travel, holiday, trip, cruise, flight or geographical locations; the *Vehicle* goal includes words like car, motorbike, scooter or their models/manufacturers; the *House* goal includes words like house, apartment, renovation, and specific furniture and appliances; the *Celebrations* goal includes words like wedding, baptism and communion; the *Family* goals includes words like daughter, son, kids, baby, and the Italian first names; the *Consumer Goods* goals includes words like iPhone, pc, camera or brands/manufacturers; the *Hobby* goals includes words like tennis, surfing and other leisure activity; the *Health* goal includes words like health, dentist, and surgery; the *Liability* goal includes words like debt, taxes and repayment; the *Entrepreneurship* goal includes words like start, project, and activity; the general *Saving* goal includes words like saving, income and investment without any further characterization.

[16]We do so by merging *Celebrations*, *Family*, *Consumer Goods*, *Health*, *Liability*, and *Entrepreneurship* into the *Other* category.

difference (-18 percentage points), while *Family* displays the smallest one (-5 percentage points). When we use the coarse scheme, which matches the pre-specified categories available on the App, we obtain point estimates almost identical to the last column of Table 8. The classification based on the LDA algorithm gives virtually identical results.

These results underscore the robustness of our finding that precise goals are achieved less often than generic goals.

(a) Commonwealth Bank of Australia

(b) Wells Fargo

(c) Chase Bank

Figure A.1: This Figure shows examples of goal setting for saving App implemented by Commonwealth Bank of Australia (a), Wells Fargo (b), and Chase Bank (c).
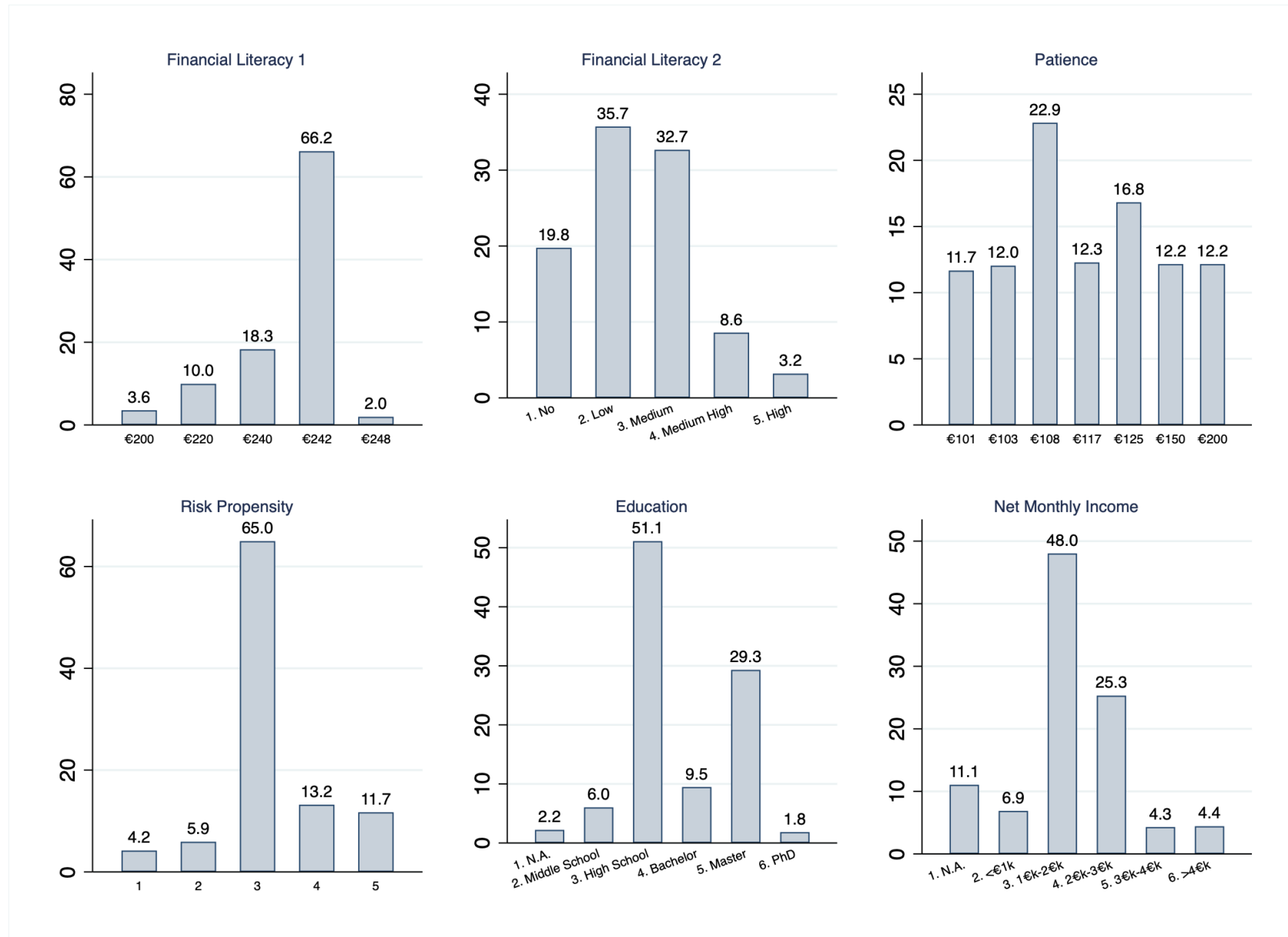
Figure A.2: This Figure shows the distribution of the answers to the survey questions relative to users' characteristics and economic preferences. The question in the upper-left plot is *"Let's say you have $200 in a savings account. The account earns 10% interest per year. If you never withdraw money or interest payments, how much will you have in the account at the end of 2 years?"* The question in the upper-middle plot is *"How knowledgeable are you about investments and financial markets?"* The question in the upper-right plot is *"Imagine, you get either $100 immediately or a higher amount of money in a month. What is the lowest amount you would be willing to wait for a month?"* The question in the lower-left plot is *"On a scale from 1 to 5, how would you rate your willingness to take risks regarding financial matters?"* The question in the lower-middle plot is *"What is your level of education?"* The question in the lower-right plot is *"What is your monthly net income?"* We display the percentage of respondents on top of each bar.

Table A.1. Fund Performance

Panel A: Fixed Income Funds

	Mean	Median	Volatility	Sharpe
12-months	0.30	-0.00	0.33	0.93
Short Term	2.43	1.81	1.84	1.32
Euro Bond	2.86	3.02	2.75	1.04
Performance	2.10	0.42	8.66	0.24

Panel B: Equity Funds

	Mean	Median	Volatility	Sharpe
America	5.71	5.04	13.90	0.41
Asia-Pacific	2.83	10.24	11.80	0.24
Europe	4.21	9.63	14.28	0.29
Active ETF	1.67	3.73	10.77	0.15
Global	4.13	7.25	9.75	0.42
Italy	0.17	15.64	17.79	0.01
Emerging Markets	4.75	8.77	12.67	0.37

Panel C: Balanced Funds

	Mean	Median	Volatility	Sharpe
Aggressive	2.54	4.08	6.90	0.37
Dynamic	2.28	3.39	5.56	0.41
Immune	0.74	0.00	1.73	0.43
Cautious	1.59	-0.37	8.40	0.19

This table presents summary statistics of the returns characteristics of the mutual funds available on the App. The funds are categorized in Fixed Income funds (Panel A), Equity Funds (Panel B) and Balanced Funds (Panel C). For each fund, we report the average and median of the annualized stock returns, annualized realized volatility—computed using daily returns—and annualized Sharpe ratios.

Table A.2 Statistics of Matched Samples (Robustness)

Panel A: Beta Testers

	Mean	Std	p5	p25	p50	p75	p95
Tenure	564.11	303.24	206.00	366.00	466.00	717.00	1,192.00
N. Accounts	1.02	0.14	1.00	1.00	1.00	1.00	1.00
Net Inflow	209.67	289.14	6.03	34.57	70.08	267.49	773.38
Risk	8.63	3.58	3.25	6.19	7.55	11.12	16.36
Gender	0.86	0.35	0.00	1.00	1.00	1.00	1.00
Age	40.91	9.42	27.00	33.00	41.00	47.00	58.00

Panel B: Matched Sample (2 Nearest Neighbors)

	t-test	Mean	Std	p5	p25	p50	p75	p95
Tenure	0.67	589.71	340.98	114.00	318.00	510.00	867.50	1,268.00
N. Accounts	-1.42	1.00	0.00	1.00	1.00	1.00	1.00	1.00
Net Inflow	-1.46	159.94	274.33	1.00	1.03	33.75	208.25	855.74
Risk	0.11	8.68	3.74	2.22	6.19	7.55	9.66	16.36
Gender	0.58	0.88	0.32	0.00	1.00	1.00	1.00	1.00
Age	-0.16	40.72	10.37	26.00	33.00	39.50	48.00	58.00

Panel C: Matched Sample (10 Nearest Neighbors)

	t-test	Mean	Std	p5	p25	p50	p75	p95
Tenure	0.80	589.34	344.23	101.00	322.00	516.00	850.00	1,269.00
N. Accounts	-1.00	1.01	0.09	1.00	1.00	1.00	1.00	1.00
Net Inflow	-1.50	165.03	289.98	1.00	4.39	35.00	175.00	858.70
Risk	-0.08	8.60	3.71	2.22	6.19	7.55	9.66	16.36
Gender	0.05	0.86	0.35	0.00	1.00	1.00	1.00	1.00
Age	-0.21	40.70	11.09	24.00	33.00	40.00	48.00	60.00

This Table presents cross-sectional summary statistics for the sample of beta testers (Panel A), and two samples of matched users (Panels B and C). We first compute the value of each variable at the user level and then report the distribution of the variable across all users. We report the mean and standard deviation of each variable, as well as the $5th$, $25th$, $50th$, and $75th$, and $95th$ percentile. *Tenure* is the number of months elapsed from the opening of user's first account to July 2017—the beginning of the beta-testing period; *N. Accounts*, is the number of accounts opened from January 2017 to July 2017; *Net Inflow* is the monthly average net deposit into the App from January 2017 to July 2017; *Risk*, is the average annual standard deviation across the mutual funds used by the user; *Gender*, is a dummy variable equal to one if male; and *Age* is age measured as of July 2017. In Panels B and C we also report the *t*-stat associated with tests on the equality of means between beta-testers and non-beta-testers along the various characteristics. To create the sample of users in Panel B (C), we use a nearest neighbor propensity score matching procedure whereby each beta-tester is matched to the closest 2 (10) matches on the App.

Table A.3. Identification Strategy II.
Results at the Account Level with Alternative Matching Specifications

Panel A. All Individuals: 2 Nearest Neighbors

	(1) Net Deposits	(2) Deposits	(3) Withdrawals
Treated Dummy	3.27**	3.59***	1.57***
	(2.31)	(2.81)	(4.00)
Constant	43.55***	46.65***	2.85***
	(37,480)	(57,490)	(3,000)
R-Squared	0.41	0.44	0.20
Obs	11,372	11,372	11,372

Panel B. All Individuals: 10 Nearest Neighbors

	(1) Net Deposits	(2) Deposits	(3) Withdrawals
Treated Dummy	3.82**	2.54*	0.00
	(2.26)	(1.68)	(0.01)
Constant	39.54***	41.79***	1.12***
	(53,735)	(65,240)	(7,305)
R-Squared	0.38	0.41	0.18
Obs	34,913	34,913	34,913

This table reports coefficient estimates and associated t-statistics (in parentheses) of the following difference-in-differences model:

$$Transaction_{i,j,t} = \alpha_i + \alpha_t + \beta \ Treated_{i,t} + \epsilon_{i,j,t},$$

where $Transaction_{i,j,t}$ denotes the monthly amount (in €) transacted by user i in account j at time t; α_i and α_t identify user and time fixed-effects; $Treated_{i,t}$ that is equal to 1 for the 122 beta testers for the 50 days (from August 1, 2017 to September 20, 2017) over which they had access to the goal-setting features of the App. The control group comprises non-beta testers matched to the characteristics of the beta-testers according to the following characteristics computed from January to July 2017: *Male*, the sex of the user; *Age*; *Account Num*, the number of accounts associated with each user; *Net Inflow*, the monthly net deposits into the account; *tenure*, the number of months the user has used the app as July 2017; and *Risk*, the average risk of the funds selected by the user. The results in Panel A focus on nearest neighbor matches that associate each beta-tester to two users on the App, while the results in Panel B focus on nearest neighbor matches that associate each beta-tester to ten users on the App. The results in the first column are based on *Net Deposits*, i.e. the difference between total *Deposits* and *Withdrawals*, while the results in column (2) and (3) only use *Deposits* and *Withdrawals*, respectively. The standard errors are double-clustered at the user and month levels. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table A.4. Effect of Goal-Setting on Saving Behavior:
Assessing the Importance of Saving Behavior Outside the App.

	Baseline	Baseline No Savings Outside	No Savings Outside	No Change in Saving Outside	Stop Saving Outside
Target Dummy× Interaction			4.61	-3.09	13.01
			(0.41)	(-0.37)	(1.24)
Target Dummy	33.98***	37.26***	34.00***	35.40***	32.27***
	(7.45)	(3.80)	(7.14)	(6.00)	(6.50)
Constant	44.62***	41.91***	43.55***	44.55***	44.70***
	(21.67)	(9.61)	(21.37)	(21.65)	(21.63)
R-Square	0.34	0.46	0.33	0.34	0.34
Obs	19,279	2,002	19,027	19,279	19,279

This table reports coefficient estimates and associated t-statistics (in parentheses) of the following panel regressions in columns 1 and 2:

$$Transaction_{i,t} = \alpha_i + \alpha_t + \beta \ Target\_Dummy_{i,t} + \epsilon_{i,t}$$

where $Transaction_{i,t}$ denotes the monthly amount (in €) transacted by individual i during month t; α_i and α_t identify user and time fixed-effects; $Target\_Dummy$ is an indicator variable equal to "0" if the user has no goals in her account at time t, and equal to "1" if she set at least one goal at time t. The results in column 1 are computed using all survey respondent data. The results in column 2 use only the survey respondents that state in the survey they have no savings outside the App. In Columns 3 through 5 we estimate:

$$Transaction_{i,t} = \alpha_i + \alpha_t + \beta \ Target\_Dummy_{i,t} + \gamma \ Target\_Dummy_{i,t} \times Interaction_i + \epsilon_{i,t}$$

where all regressors are defined as in the previous regression specification and the only difference stands in the variable $Interaction_i$. In column 3, $Interaction_i$ is equal to 1 for those individuals who respond they have no savings outside the App and is equal to zero otherwise. In column 4, $Interaction_i$ is equal to 1 for those individuals who respond they do not change their saving rate outside of the App after adopting the App and is equal to zero otherwise. In column 5, $Interaction_i$ is equal to 1 for those individuals who respond they reduce their savings outside the App after adopting the App and is equal to zero otherwise. The standard errors are double-clustered at the user and month levels. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table A.5. Determinants of Goal Achievement: Robustness

	Panel A: Manual			Panel B: Machine Learning	
	Fine	Coarse		Fine	Coarse
Hobby	-0.07***	-0.07***	Topic 1	-0.11***	-0.11***
	(-2.81)	(-2.81)		(-11.88)	(-11.45)
Travel	-0.14***	-0.13***	Topic 2	-0.11***	-0.12***
	(-13.36)	(-13.30)		(-8.03)	(-9.53)
Other	-0.06***	-0.08***	Topic 3	-0.11***	-0.10***
	(-4.30)	(-7.84)		(-7.77)	(-6.46)
Car	-0.13***	-0.13***	Topic 4	-0.11***	-0.10***
	(-9.58)	(-9.51)		(-5.80)	(-4.89)
House	-0.11***	-0.10***	Topic 5	-0.07***	-0.09***
	(-6.20)	(-6.17)		(-3.14)	(-3.54)
Celebration	-0.08***		Topic 6	-0.09***	
	(-4.30)			(-2.76)	
Consumer Goods	-0.12***		Topic 7	-0.08**	
	(-7.70)			(-2.09)	
Entrepreneurship	-0.11**		Topic 8	-0.09*	
	(-2.43)			(-1.72)	
Family	-0.05**		Topic 9	0.06	
	(-2.12)			(1.01)	
Liability	-0.13***		Topic 10	-0.06	
	(-3.45)			(-0.58)	
Health & Wellbeing	-0.18***		Topic 11	-0.20***	
	(-4.95)			(-3.54)	
Constant	0.02	0.01		-0.00	-0.02
	(0.17)	(0.08)		(-0.01)	(-0.13)
Controls	✓	✓		✓	✓
Time FE	✓	✓		✓	✓
Province FE	✓	✓		✓	✓
R-Square	0.18	0.18		0.18	0.18
Obs	12,940	12,940		12,940	12,940

This table reports coefficient estimates and associated t-statistics (in parentheses) of the following linear probability model:

$$p_i = Pr\left(y_i = 1 | \boldsymbol{x}_i\right) = \boldsymbol{x}_i'\boldsymbol{\beta} + \boldsymbol{c}_i'\boldsymbol{\gamma} + \alpha_{time} + \alpha_{province} + \epsilon_i$$

where the dependent variable is 1 if goal i is achieved and 0 otherwise. The vector $\mathbf{x}_i$ contains the dummies for the categories of goals described in Section Appendix A. In all specifications, the generic *Saving* category is the base case. The set of controls ($\boldsymbol{c}$) include the log transformation of the goal horizon, measured in days; the log transformation of the goal amount; the age of the user; and a gender dummy. α_{time} and $\alpha_{province}$ denote monthly and province fixed-effects, respectively. All the continuous variables have been standardized to have a standard deviation of one. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Section 1 of 4: Saving Behavior Outside Gimme5

Q1.1 **Since using** Gimme5, how much have you saved on average per month **outside the App**?
- €0
- Between €1 and €49
- Between €50 and €100
- Between €101 and €150
- More than €150
- Do not know / Do not remember

Q1.2 **Before using** Gimme5, how much have you saved on average per month **outside the App**?
- €0
- Between €1 and €49
- Between €50 and €100
- Between €101 and €150
- More than €150
- Do not know / Do not remember

Q1.3 **Since using** Gimme5, have you changed how much you saved **outside the App?**
- Yes, decreased
- No
- Yes, increased
- Do not know / Do not remember

Q1.4 Which channels do you use to invest your savings **outside the App?**
(please select one or more)
- I do not save outside the App
- Bank Saving Account
- Trading Platform
- Financial Advisor
- Other Apps
- Other _____

Section 2 of 4: Usage of Saving Goals

Q2.0.1 How many saving goas have you created so far?
- 0
- 1
- 2
- 3
- 4
- 5 or more

-- Note: Questions Q.2.1.1 to Q.2.1.3 below are only visible for those who chose 0 in Q2.0.1 --

Q2.1.1 Why have not created a saving goal yet?
- I did not know
- I'm not interested in saving for a specific goal
- It is too difficult
- I do not know
- Other _____

Q2.1.2 If you decided to create a saving goal, what aspect would you find more motivating?
- Having a deadline
- The nature of the goal
- The ability to monitor my progress towards the goal
- I do not know
- Other _____

Q2.1.3 What decision associated with creating a saving goal do you find more challenging?
- Deciding the amount
- Deciding the nature of the goal
- Deciding the horizon
- I do not know
- Other _____

--- Note: Questions Q.2.2.1 to Q.2.2.4 below are only visible for those who chose 1, 2, 3, 4, 5 or more in Q2.0.1 --

Q2.2.1 In your experience, what is the most motivating aspect of having a saving goal?
- Having a deadline
- The nature of the goal
- The ability to monitor my progress towards the goal
- Other _____
- I do not think having a goal is motivating

Q2.2.2 Think about the saving goals you **have achieved.** In your opinion, what has been the most decisive factor?

- The deadline
- The nature of the goal
- The ability to monitor my progress towards the goal
- The return of the fund
- I have never achieved my saving goals
- I do not know
- Other _____

Q2.2.3 Think about the saving goals you **have NOT achieved.** In your opinion, what has been the most decisive factor?

- Lack of initial motivation
- The amount of the goal was too high compared to the horizon
- I faced unexpected expenses
- The return of the fund
- I have always achieved my saving goals
- I do not know
- Other _____

Q2.2.4 Since you started using saving goals your use of Joinks

- Is decreased a lot
- Is decreased a little
- Is remained constant
- Is increased a little
- Is increased a lot
- Do not know
- I do not use Joinks

--- Note: Questions Q.2.3.1 to Q.2.3.3 below are visible to all respondents --

Q2.3.1 What feature of the App do you find most helpful in increasing your saving?

- Saving small amounts through Joinks
- Investing in mutual funds
- Saving goals
- Automatic saving rules
- Do not know
- Other _____

Q2.3.2 How can we help you to achieve your goals?
(Please select one or more)

- Suggesting the horizon of the goal
- Suggesting the amount of the goal
- Suggesting how much to save per month based on the horizon and the amount of the goal
- Sending a monthly reminder on how much to save
- Do not know
- Other _____

Q2.3.3 What innovations would you like to be implemented in the next release of the App?
 (Specify below or leave empty)

_____

_____

_____

Section 3 of 4: Usage of the Joink Function

Q3.0.1 Do you find the Joink Function easy to understand?

- Yes
- No
- Do not know

Q3.0.2 On average, how many times in a month do you use the Joink function?

- Never
- Between 1 and 5
- Between 6 and 10
- More than 10

--- Note: Question Q3.1.1 below is only visible for those who chose "Never" in Q3.01. --

Q3.1.1 Why do you not use the Joink function?

- I do not know what it is
- I do not know how to use it
- I do not think it is useful
- I do not now
- Other _____

--- Note: Questions Q3.2.1 and Q3.2.2 below are only visible for those who did not choose "Never" in Q3.01. --

Q3.2.1 When do you use the Joink Function?
- When I give up a daily expense
- When I perform a daily expense
- When I give up an occasional expense
- When I perform an occasional expense
- My use of the Joink function is unrelated to any specific situation
- Other _____

Q3.2.2 What is the main reason you use Joinks?
(Specify below or leave empty)

_____

_____

_____

Section 4 of 4: Your Opinion on Financial Markets

Q4.1 Let's say you have $200 in a savings account. The account earns 10% interest per year. If you never withdraw money or interest payments, how much will you have in the account at the end of 2 years?
- €200
- €220
- €240
- €242
- €248

Q4.2 How knowledgeable are you about investments and financial markets?
- Not an expert
- Low
- Medium
- Medium High
- High

Q4.3 Imagine you get either $100 immediately or a higher amount of money in a month. What is the lowest amount you would be willing to wait for a month?
- €101
- €103
- €108
- €117
- €125
- €150
- €200

Q4.4 On a scale from 1 to 5, how would you rate your willingness to take risks regarding financial matters?
- 1, I avoid risk at all costs
- 2
- 3, I try to balance risk and returns
- 4
- 5, I want the highest possible returns even if it entails a high level of risk

Q4.5 What is your highest level of education?
- Middle School
- High School
- Bachelor
- Master
- PhD
- Prefer not to answer

Q4.6 What is your net monthly income?
- Less than €1.000
- Between €1.000 and €2.000
- Between €2.000 and €3.000
- Between €3.000 and €4.000
- More than €4.000
- Prefer not to answer