Set it and Forget it: Engineering Investment Habits with FinTech*

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August 23, 2025

Abstract

We study how automated investment rules affect saving behavior and investment outcomes using detailed data from a FinTech app designed to help retail investors access mutual funds. Users choose how to design these rules, which vary along dimensions such as frequency, amount, and triggering conditions. Using a randomized encouragement design, we show that automated rules *causally* increase average savings without crowding out manual contributions. We also show that automated rules reduce trend-chasing behavior: while manual deposits respond strongly to recent returns, automated ones do not, narrowing the gap between fund returns and realized investor returns. However, rule timing remains performance-sensitive—users tend to activate rules after periods of strong returns and suspend them during downturns, especially for equity funds. A survey deployed on the app user population reveals that adopters of automated investment rules are primarily motivated by a desire to avoid procrastination, reduce cognitive load, and simplify decision-making, while non-adopters cite preferences for flexibility and concerns about income volatility. Our findings highlight both the promises and the limitations of automation in improving individual financial outcomes.

Keywords: FinTech, Saving and Investment Behavior, Habit Creation
JEL Classification: D14, G41, G51

*We acknowledge financial support from the University of Houston Behavioral Research Assistance Grants. We thank FIDA for providing access to the Funds Datafeed. We are incredibly grateful to Giuseppe Codazzi and Marco Viganò for many fruitful discussions and for answering our questions about the data. All errors are our own.

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"We are what we repeatedly do, therefore excellence is not an act, but a habit"

Will Durant

Saving, like exercising or following other virtuous behaviors, requires a periodic sacrifice (monetary or in terms of effort) in the present for the attainment of a future benefit. Not surprisingly, recent statistics highlight that a majority of U.S. adults lack sufficient savings to withstand income shocks and are unprepared for retirement.[1] Moreover, when investing their savings, retail investors, especially those less sophisticated, are prone to biases and mistakes.[2] Most notably, they display return-chasing behavior in the cross-section (by increasing exposure to assets with better recent relative performance) and in the time series (by entering and exiting positions based on past performance) in both retirement (see e.g., Choi et al., 2009 and Tran and Wang, 2023) and brokerage accounts (see e.g. Bailey, Kumar, and Ng, 2011 and Choi and Robertson, 2020a).

What if (good) investment habits could be automated? In this paper, we explore this possibility using a unique dataset from a FinTech App that offers the opportunity to create automated investment rules. Setting an investment rule entails deciding on the amount and frequency of the deposits (or the event triggering them), and selecting the assets to invest in. This form of automation has also been recently introduced by some of the largest U.S. brokerages.[3] The typical arguments in favor of automated investment rules are that they help address investors' limited attention problems and mitigate the temptation to time the market. On the other hand, individuals might design suboptimal rules or adjust them in response to recent market movements, potentially undoing the benefits of automation.

Understanding whether automated investment rules can help investors save more and achieve better performance is important for at least three reasons. First, thin saving buffers reduce households' ability to absorb negative income shocks (Baker (2018)) and increase reliance on expensive forms of debt.

[1] The CFPB report linked (here) shows that 63% of Americans have less than one month of income saved.

[2] See Benartzi and Thaler (2007) for a review of the literature on individual investors in retirement accounts and Barber and Odean (2013) for the literature on brokerage accounts.

[3] For example, Robinhood (`https://robinhood.com/us/en/support/articles/recurring-investments/`), Vanguard (`https://investor.vanguard.com/investor-resources-education/portfolio-management/making-regular-investments`), J.P. Morgan Chase (`https://www.chase.com/personal/investments/learning-and-insights/article/why-setting-up-recurring-transfers-could-be-a-winning-strategy`) and Interactive Brokers (`https://www.interactivebrokers.com/en/trading/recurring-investments.php`)

Moreover, the increase in life expectancies and decrease in birth rates experienced by many developed countries are expected to strain government-sponsored pension programs, requiring individuals to seek alternative sources of retirement income (Gargano and Giacoletti, 2024). Second, individual investors often struggle with cognitive biases and emotional decision-making, leading to suboptimal investment behaviors such as chasing past returns or panic selling during market downturns (An, Lou, and Shi, 2022; Hoopes et al., 2022). By automating investment decisions through predefined rules, investors can mitigate these biases, promote disciplined saving, and potentially achieve better long-term performance. Finally, since investment rules are now being deployed on a large scale by traditional banks and institutions, millions of individuals are being exposed to these tools. Therefore, understanding their impact is crucial for both individual financial well-being and the broader financial system.

The App we study was developed by an Italian asset manager and designed to help small investors access mutual funds. A unique feature of the app is that users can set deterministic rules for scheduled deposits—monthly, weekly, daily, or on specific dates—or stochastic rules triggered by specific conditions, such as a sports team's win or reaching a daily step goal. While automated saving rules are theoretically suboptimal in standard life-cycle models (Gomes, 2020)—because they constrain flexibility (Amador, Werning, and Angeletos, 2006)—they may appeal to investors who struggle with present bias (Laibson, 1997), limited attention (Abel, Eberly, and Panageas, 2007, 2013), or self-control (Gul and Pesendorfer, 2001). In practice, these rules offer a way to commit to future savings while minimizing the cognitive burden of constant reoptimization. Our setting provides a natural laboratory to examine whether, and how, investors are willing to trade flexibility for commitment.

On the extensive margin, 41% of the app users adopt investment rules and, among rule adopters, the majority rely on more than one rule, automating 73% of their deposits, highlighting a strong preference for automation. The most popular rule is monthly deposits, used by 86% of the adopters and accounting for 85% of the automated deposits. In contrast, rules triggered weekly or daily, along with those based on special dates, activity goals, or sports results, are far less common on their own; when implemented, they often serve as complements to monthly deposits rather than standalone strategies.

A key aspect of saving rule design is the trade-off between the intensive margin—the amount saved per deposit—and the extensive margin—the frequency of deposits. We find that monthly rules involve larger contributions per deposit (€58.5) than weekly (€16.8) and daily rules (€6.1). However, monthly rules result in lower aggregate savings over time (€497.5) than weekly (€516.5) or daily rules (€556.3). This pattern emerges even though investors tend to overestimate their ability to maintain more frequent contributions: daily rules are typically discontinued after 5 months, while weekly and monthly rules remain active for 8 and 9 months, respectively. Event-based rules—triggered by special dates, steps walked, or sports outcomes—represent a small fraction of total deposits, confirming that users treat them as supplementary rather than primary tools for long-term saving.

An important consideration in evaluating the effectiveness of investors' saving rules is how they interact with both fund choice and investment performance. Regarding the first, we find that investors are more likely to create saving rules in equity funds (49%), compared to balanced (46%) and fixed-income funds (42%). This relation suggests that investors are more inclined to automate contributions in higher-risk funds, where poor market timing can have more severe consequences. Turning to the second, we also find that investors frequently establish new rules following strong performance—particularly for equity funds—and discontinue them when returns turn negative, suggesting that while saving rules are intended to mitigate market timing, their effectiveness may be compromised by investors' tendency to time the rules themselves.

In the second part of the paper, we study whether savings rules have a positive effect on saving rates. We begin by showing the reduced form results relating deposits, withdrawals, and net savings to whether app users have active savings rules. We find that automated rules boost total deposits by around €87.74 per month—relative to an average deposit of €26.54 in the absence of a rule—with only a minimal reduction in manual deposits. At the same time, rule activation is linked to a notable drop in withdrawals, leading to an overall net savings increase of roughly €102.42 per month.[4]

The reduced form results cannot be interpreted as causal because the decision to create a rule is inherently endogenous. Investors might adopt these rules in response to individual-specific, time-

[4]When we focus on users who engaged in manual deposits for at least two, four, or six months before adopting automated rules—and hence exclude those who test the app with a few small manual transactions and immediately adopt an automated saving rule—we find that while the effect moderates with users' prior engagement, it remains sizeable—indicating that automated recurring investment rules hold significant promise in increasing users' saving rates.

varying shocks—such as income shocks or changes in financial goals—that are not directly observable in the reduced-form regressions. To address this issue, we implement a Randomized Encouragement experiment (Imbens and Angrist, 1994; Duflo and Saez, 2003; Fowlie, Greenstone, and Wolfram, 2018) on the new users who signed up for the app between September and December 2024. During this period, all (new) users had access to recurring savings rules, but only a randomly selected subset received notifications highlighting their benefits and encouraging their usage. We use these notifications as an instrumental variable, allowing us to isolate the portion of rule adoption that is uncorrelated with users' innate saving tendencies and thus estimate the causal impact of automated rules on saving behavior.

Our first-stage estimates confirm that notifications increased the adoption of savings rules by nearly 15%, roughly doubling the baseline adoption rate of 15.4%. Leveraging this random variation, we employ an Instrumental Variables (IV) framework to isolate the causal impact of rule adoption on saving. The IV results indicate that adopting automated saving rules *causes* a significant rise in deposits, while withdrawals remain largely unchanged. As a result, the net effect is a meaningful increase in total savings. In addition to the IV estimates, we assess the broader effect of receiving a notification through an Intent-to-Treat (ITT) analysis, which considers all users encouraged by the notification—whether or not they ultimately adopt a rule. Our results show a notable increase in average daily deposits among the encouraged group.

In the third part, we explore the effect of automated deposits on users' investment performance. Unless they buy and hold a given position for the entire period, investors realize returns that differ from those of the funds they invest in due to the timing of their deposits and withdrawals. Prior evidence shows that retail investors display trend-chasing behavior because of extrapolative expectations: investors interpret past positive performance as a predictor of future performance (Choi et al., 2009; Tran and Wang, 2023; Bailey, Kumar, and Ng, 2011; Choi and Robertson, 2020a). Since mutual fund performance displays little persistence (Bollen and Busse, 2004; Busse, Goyal, and Wahal, 2014), trend-chasing typically leads to lower returns than those realized by the fund (Morningstar, 2024). Activating automated saving rules is a simple way for investors to implement a "dollar-cost averaging" strategy, which is beneficial because, when prices are high, fewer shares or units are bought, and when

prices are low, more are purchased. Overall, this strategy tends to lower the average entry cost over time and mitigates trend-chasing.

We first show that automated rules eliminate investors' trend-chasing behavior. Manual deposits strongly correlate with past performance up to six months, particularly in equity funds. This indicates that investors tend to deposit more in periods of good market returns, i.e., trend-chase. On the other hand, recurring deposits show little to no link with past returns, implying that once a rule is active, investors no longer time their deposits based on fund performance.

We then show that automated rules narrow the "return gap" between the fund performance and the dollar-weighted returns realized by the investors, i.e., the return that accounts for investors' timing of deposits and withdrawals. The gap equals 1.5% per year for those who deposit manually and shrinks to 0% for those who instead fully automate their deposits, suggesting that automated investment strategies help circumvent harmful market-timing decisions. This effect is robust across different fund types, with particularly pronounced benefits when fund performance is negative. Taken together, these findings provide strong evidence that automation not only stabilizes users' contribution patterns but also improves investors' outcomes by improving the returns they realize.

To complement our administrative data, we conducted a survey of app users to better understand the psychological and behavioral motivations behind rule adoption. These insights are crucial for designing interventions that can expand usage and, ultimately, improve long-term financial outcomes. Among adopters, the most frequently cited motives include avoiding procrastination (Laibson, 1997; Ashraf, Karlan, and Yin, 2006; O'Donoghue and Rabin, 1999), overcoming limited attention (DellaVigna and Pollet, 2009; Abel, Eberly, and Panageas, 2007, 2013), and reducing the psychological burden of ongoing financial decision-making (Bertrand, Mullainathan, and Shafir, 2004; Shah, Mullainathan, and Shafir, 2012; Kahneman, 2011). In contrast, more strategic considerations—such as implementing dollar-cost averaging (Statman, 1995), increasing motivation (Thaler and Benartzi, 2004a; Karlan et al., 2016), or avoiding market timing (Shefrin and Statman, 1985; Barber and Odean, 2001)—are viewed as secondary. Among non-adopters, the most common explanations are a preference for flexibility (Gul and Pesendorfer, 2004), confidence in their own financial discipline (Van Rooij, Lusardi, and Alessie, 2011), and income volatility that makes committing to fixed rules difficult (Carroll, 1997;

Dynan, Skinner, and Zeldes, 2004).

We also examine how individuals' expectations and beliefs about market timing and return predictability, as well as their sophistication as measured by their mutual fund selection criteria (Bailey, Kumar, and Ng, 2011) and demographic characteristics, relate to the adoption of automated savings rules. We first show that investors do not view automated savings rules as tools for improving market timing or exploiting predictable returns. We then show that rule adopters tend to be more financially secure and sophisticated, pointing to two complementary policy recommendations. First, financial education efforts should emphasize that automated savings tools not only help individuals overcome behavioral frictions but also promote consistent investing and reduce harmful market timing attempts. Second, targeted outreach should focus on financially vulnerable and less sophisticated individuals—those least likely to adopt these tools but potentially most in need of the structure and discipline they provide.

1 Contributions to the Literature

Our paper contributes to three broad literatures in economics and finance. First, we contribute to the literature on retail investors in mutual funds, which are a key component of the household balance sheet in the United States. In 2022, 52.3% of U.S. households owned mutual funds, either directly or indirectly through their retirement accounts.[5] Using different approaches, the literature has extensively documented trend-chasing behavior, i.e., the tendency to invest (divest) in response to past positive (negative) returns.[6] Cooper, Gulen, and Rau (2005), Frazzini and Lamont (2008), Ivkovic and Weisbenner (2009), and Ben-David et al. (2022) study aggregate fund flows and show that funds with better past performance, i.e., past winners, also experience abnormally higher inflows.[7] Bailey, Kumar, and Ng (2011), Heuer, Merkle, and Weber (2017), and Choi and Robertson (2020a), study individual positions in brokerage accounts and survey data and show that trend-chasing behavior is driven by the expectation that past performance signals skills and would persist in the future. Finally, Agnew and Balduzzi (2003), Choi et al. (2009), Dahlquist, Martinez, and Soderlind (2017) and Tran

[5] See `https://www.ici.org/news-release/22-news-ownership`

[6] Trend-chasing behavior by retail investors is not limited to mutual funds: it has also been documented in stocks (see Benartzi (2001) and Barber and Odean (2008)) and illiquid assets like real estate Piazzesi and Schneider (2009).

[7] See Choi and Kronlund (2018) for evidence on bond mutual funds.

and Wang (2023) provide evidence of trend-chasing in retirement accounts.[8] Trend-chasing is harmful to investors because mutual fund performance is not persistent over horizons of one year or longer (see, e.g., Bollen and Busse (2004); Busse, Goyal, and Wahal (2014)). As a consequence, when investors try to time the market based on past performance, they often generate large negative gaps between their actual returns and the returns generated by the funds (see Morningstar (2024)). Rather than providing further evidence on trend-chasing, we demonstrate that recurring investment rules can attenuate this behavior. Our findings have implications not only for the welfare of retail investors but also for the funds' industry and stability of markets, as managers' trading decisions in response to large in- and outflows have been shown to have distortionary effects on asset prices (see, e.g. Coval and Stafford (2007a)).

Second, we contribute to the literature on household saving behavior. A first strand of the literature studies the adequacy of households' savings for retirement (see, e.g., Bernheim, Skinner, and Weinberg, 2001, Scholz, Seshadri, and Khitatrakun, 2006 and Lusardi and Mitchell, 2007) as well as their ability to withstand unexpected negative income shocks (Lusardi, Schneider, and Tufano (2011)). A second strand focuses on the behavioral biases explaining undersaving, such as present bias (Laibson, 1997), over-extrapolation Choi et al. (2009), limited cognitive ability, willpower, and self-efficacy (Benartzi and Thaler, 2007; Kuhnen and Melzer, 2018). More recently, attention has focused on how to help households save more. The solutions proposed include reminders (Karlan et al., 2016 and Medina and Pagel, 2024), nudges (Madrian and Shea, 2001, Thaler and Benartzi, 2004b, Duflo et al., 2006 and Beshears et al., 2022) savings accounts embedding lottery-type features (Cookson, 2018 and Higgings et al., 2024) or commitment devices (Ashraf, Karlan, and Yin, 2006), peer pressure (Duflo and Saez, 2003) and financial innovation (Parker, Schoar, and Sun (2023)). We contribute to this literature by providing evidence on recurring investment rules, which have been unexplored so far.

Finally, we contribute to the literature on habit formation. Due to the social costs of unhealthy lifestyles—such as smoking, drinking, poor diets, and lack of exercise—a substantial body of economic literature examines how to establish healthy habits. Based on theories of cue-based habit formation,

[8] In retirement accounts, investors can select funds from a limited set decided by the plan sponsor. Elton, Gruber, and Blake (2007), and Goyal and Wahal (2008) show that past performance predicts whether funds are included (excluded) from the set of funds offered. Show that Pool, Sialm, and Stefanescu (2016) the sensitivity of the deletion decision to past performance is weaker when a fund belongs to the family of the plan sponsor.

these studies test the efficacy of incentives, positive reinforcement, and contextual cues in creating habits. For example, see Della Vigna and Malmendier (2006), Charness and Gneezy (2009), and Beshears et al. (2021) for evidence on exercising; Loewenstein, Price, and Volpp (2016) on healthy eating; Giuntella, Saccardo, and Sadoff (2024) on sleeping; and Schilbach (2019) on alcohol consumption. However, these studies often find disappointing long-term results, with individuals reverting to old patterns of behavior once incentive programs end. We contribute to this literature by providing evidence in the domain of saving, where habits can be automated rather than solely formed.

2 Setting and Data

In this section, we introduce the App, describe the survey administered to the user population, detail the data used in our analysis, and present key summary statistics.

2.1 The App and the Recurring Investments Feature

The data for this study comes from AcomeA, an Italian asset manager that created the savings app Gimme5. The app works like a digital piggy bank, allowing users to save small amounts—starting at 1 euro. Signing up is free, with no activation or annual fees.[9] Once registered, users can deposit money at any time from their linked bank account, similar to a checking or savings account. However, instead of keeping funds in a traditional account, investors allocate their savings into different mutual funds with varying risk and return levels.

A crucial aspect of our study is that users can create recurring investment rules on the App by specifying two parameters: the deposit amount and the event that triggers the deposit. Rules can be deleted at any time without paying any fee, and users can have multiple active rules at the same time. This functionality is very similar to the one offered by many other savings Apps and brokerages, such as Acorns, Vanguard, JP Morgan Chase, Robinhood, and Interactive Brokers.

Users can create six types of rules, four of which are deterministic and have a pre-specified fixed frequency: monthly (MONTH rule), weekly (WEEK), or daily (DAILY). The last deterministic rule, DATE, deposits the specified amount on a specific date selected by the user. Two rules are "stochastic"

[9] The only cost is a flat €1 fee for withdrawals, regardless of the amount.

in that the deposits are transferred only if a condition is satisfied. For the SPORT (SPR) rule, the transfer happens if the sports team selected by the user wins, while for the FIT rule, the transfer happens if the user walks a minimum number of steps—set by the user—in a day.

2.2 The Survey

We complement the administrative data with a survey administered to a sample of App users.[10] As in Liu et al. (Forthcoming), matching survey responses with observed behaviors in the App allows us to investigate the economic mechanisms behind individuals' choices.[11]

The survey was conducted between July 16 and July 31, 2025. We invited 27,000 users via email, and sent three reminders—on the first day, after one week, and one day before the end of the field period. We obtained a total of 1,215 responses, for a response rate of 4.5%, which is within the typical range for online surveys. For instance, McCahery, Sautner, and Starks (2016) achieved a response rate of 4.3% in their study of institutional investors, while Giglio et al. (Forthcoming) obtained response rates between 2.5%-4% for retail investors.

The survey comprises three sections (see Appendix B for the full list of questions in the original language and English). In the first, we ask whether respondents have ever used the App's recurring rule feature. Based on their answer, they are directed to a corresponding set of follow-up questions eliciting their motives.[12] To avoid priming respondents with predefined mechanisms, we begin with an open-ended question asking them to describe their reasons for adopting a rule (or otherwise), following the approach of Stantcheva (2023), Haaland, Roth, and Wohlfart (2025) and Bergman et al. (2020). This is followed by a Likert-scale matrix rating a predefined set of motives, whereby respondents are asked to rate each one on a scale from 1 (very irrelevant) to 5 (very important).[13]

Those who have used the feature are asked to assign a score to the following statements on rules, including: (i) *Help avoid procrastinating on saving*, (ii) *Save time by reducing the need to monitor the markets*, (iii) *Eliminate the stress and mental burden of making decisions each time*, (iv) *Are fun and*

[10] The full translated survey is included in the Online Appendix.

[11] See also Coibion, Gorodnichenko, and Weber (2019), Coibion et al. (2020), Choi and Robertson (2020b), Brauer, Hackethal, and Hanspal (2022), Giglio et al. (2021), Giglio et al. (Forthcoming), D'Acunto, Malmendier, and Weber (Forthcoming) and Hackethal et al. (2025).

[12] A third option, "*Don't Know / Don't Remember*," was available to avoid forcing responses. These users are not shown the questions related to the motives for their choice.

[13] A bipolar scale helps avoid priming respondents in a particular direction (Dillman, Smyth, and Christian, 2014).

motivating, (v) *Take advantage of volatility to lower the average purchase price (dollar-cost averaging)*, and (vi) *Avoid the temptation to time the market.* Respondents who have canceled a rule are also asked to indicate the reasons for cancellation.

Those who have never used the rule feature are similarly asked to assign a score to the following statements: (i) *I don't know how to create the best rule for me*, (ii) *I'm already disciplined and invest regularly*, (iii) *I want to decide how much to save based on circumstances*, (iv) *My income is too variable*, (v) *I don't have money to save*, (vi) *I don't understand how it works*, and (vii) *I don't know what a savings rule is.*

The second section of the survey focuses on beliefs about investment behavior. We elicit views on market timing, asking whether respondents try to time the market and whether they think they have the tools to do it successfully using the following questions "*To what extent do you follow a market timing strategy, that is, trying to identify the best moment to enter or exit the markets in order to maximize returns?*" and "*Do you think you have the tools to predict market trends?*"[14]

We then ask two questions on mutual funds. We first ask whether they believe that past returns predict future performance.[15] We also ask them to identify the most important factors they consider when investing in a mutual fund.[16]

In the final section, we collect demographic information and psychological traits that are not observable in administrative data but have been shown in prior literature to be associated with undersaving. Commonly cited reasons for individuals' inability to save include low levels of financial literacy (Lusardi, 2008; Lusardi and Mitchell, 2014), high levels of impatience (Laibson, 1997), limited education (Cole, Paulson, and Shastry, 2014), as well as low income and socioeconomic status (Duflo and Banerjee, 2011; Kuhnen and Miu, 2017).[17] Appendix Figure A.1 summarizes key characteristics of the survey respondents.

[14]The options to choose from for the first question are: (i) *Never*, (ii) *Rarely*, (iii) *Sometimes*, (iv) *Often*, and (v) *Always*. and they are: (i) *Definitively No*, (ii) *No*, (iii) *Maybe*, (iv) *Yes*, and (v) *Definitively Yes.*

[15]The exact question is "*Do you think that a fund's past returns predict its future returns?*" with the following options: (i) *Never*, (ii) *Rarely*, (iii) *Sometimes*, (iv) *Often*, (v) *Always*, and (vi) *I don't know.*

[16]*Risk profile*, *Past performance*, *Performance relative to the benchmark*, *Investment style*, *Fees and commissions*, *Ratings from external agencies (e.g., Morningstar)*, *Manager's experience*, *Reputation and recognition of the management company*, *Fund name.*

[17]We measure financial literacy using the first of the "big three" financial literacy questions (Lusardi and Mitchell (2014)) and asking respondents to self-assess their expertise about financial markets. We measure impatience by asking respondents to select between $100 today and a higher amount in the future.

2.3 Data Sources

The data comprises five tables named *Rules*, *Deposits and Withdrawals*, *Investment Vehicle*, and *Users*. The company anonymized all information to guarantee user privacy. The sample period begins in January 2021 and ends in December 2024.

The *Rules* table contains information on the rules set by the users. For each rule, we observe its inception date, the type (MONTH, WEEK, DAILY, DATE, SPORT, or FIT), the amount of each deposit, and other rule-specific properties. For instance, for SPORT, we observe the team the rule is associated with; for FIT, we observe the number of steps. The *Deposits and Withdrawals* table contains information on all the deposits and withdrawals associated with each user at the daily frequency. For each transaction, we have information on which account and/or rule it is associated with and the amount withdrawn or deposited. The *Users* table contains information on the users who created a profile on the App. The main variables in this table are the dates of opening and closing for every account created by each user.[18] Additional information includes users' age, gender, enrollment date, location of residence, place of birth, and other questions related to Know Your Customer (KYC) compliance. The *Investment Vehicle* table contains information on the name and identifier of the mutual fund associated with each account.

We complement the App data with the Funds Datafeed from FIDA (Finanza Dati Analisi), which provides daily mutual fund returns for the funds the App users can invest in.[19]

2.4 Summary Statistics

Panels A and B in Table 1 show cross-sectional summary statistics at the user level for all users with at least one transaction over our sample period. We first compute the value of each variable at the individual level and then report the resulting cross-sectional distribution. For each variable, we report the number of observations used in the second step of the computations, the mean, standard deviation, and the $1st$, $25th$, $50th$, $75th$, and $99th$ percentiles.

Panel A shows that users are relatively young, with an average age of 36, consistent with the

[18] The backend of the App creates a different account for each mutual fund chosen by the user. From the user's point of view, however, there is no difference as she logs in with a single username and password.

[19] For more information, visit the following link: `https://www.fidaonline.com/en/data.html`

literature showing a strong relation between age and FinTech adoption (see Crouzet et al., 2024, Becker, 2017 and Olafsson and Pagel, 2018). Only 18% of the users are females, suggesting that women are either less targeted by Financial Apps or are less interested in these tools in Italy.

Panel B reports results on App activity computed over the 48 months between January 2021 and December 2024. The average investor is present in our data for almost two years (20 months), with some users maintaining an account for only one month (at the 1st percentile of the distribution) and some being active over the full sample (48 months at the 99th percentile). The average investor makes 2.6 deposits per month, while those in the top 1% deposit more than €1,152 per month.

On average, users invest in 1.5 funds, with the median investor choosing only one fund. The average user invests 12% of their deposits into equity funds, 46% in fixed-income, and 43% in balanced funds. These categories comprise funds with different specific strategies. Equity funds are divided by the Asset Manager into geographic areas, such as the US, Europe, Italy, Asia-Pacific, Emerging Markets, and International, and invest 90% or more of their assets in equity instruments. Balanced funds allocate between a minimum of 40% ("strategia moderata" and "patrimonio esente") to a maximum of 70% in equity ("strategia crescita" and "strategia dinamica globale") and the rest in fixed-income instruments. Fixed-income funds are divided into short-term ("risparmio" and "breve termine") and medium-long term ("performance") and can allocate up to 15% in equity (performance).

Panel C reports the net-of-fees performance of the different funds in each category. Starting from Equity funds in Panel C.1, all funds have volatility higher than 10% per year and average annual returns that range from 1.65% to 8.53%. Balanced funds instead have a lower volatility that ranges from 4.66% to 7.90% and returns that range from 0.39% to 11.15%. "Strategia Crescita" is the best-performing fund in this category, with a Sharpe ratio of 1.41. Finally, the fixed-income funds have a volatility that ranges between 0.36% and 7.16% and returns that range between -2.58% and 2.51%.[20]

3 Adoption, Design and Timing of Investment Rules

A key aspect of our setting, similar to other banks and FinTechs using this tool, is that users are responsible for choosing the type and number of rules to adopt, their design- i.e., the frequency and

[20]It is not unusual for fixed-income funds to generate a high Sharpe ratio, as it is the case for the "Risparmio" fund, because of their low volatility.

amount of the periodic deposits- when to create (or delete) them, and the fund in which to invest their deposits. A possible concern is that while rules are, in principle, aimed at helping users achieve their desired saving rates, they might lead investors to make mistakes and save sub-optimally. To this end, we explore the intensive and extensive margins of rule adoption in Section 3.1, how users design rules in Section 3.2, and the relation between rules and the fund's profile in Section 3.3.

3.1 Adoption and Usage of Rules

In standard life-cycle models of consumption and portfolio choice, individuals dynamically optimize their consumption and investment decisions based on expected future income and returns to maximize lifetime utility (Gomes, 2020). Under these conditions, automated saving rules inherently impose constraints, thus making them suboptimal from a theoretical standpoint, as they limit the flexibility required for continuous optimization. However, extensive empirical evidence highlights significant deviations from this benchmark, driven by behavioral and other frictions that prevent continuous dynamic optimization. Broadly, these deviations can be grouped into three main categories.

First, individuals frequently exhibit present-biased preferences and self-control issues, disproportionately valuing immediate consumption over future welfare. Such biases lead individuals to consume excessively in the short run and subsequently regret their lack of discipline, thereby rationalizing a strong demand for automated saving rules that serve as commitment devices (Laibson, 1997). Second, individuals face substantial attention and information processing constraints, which make it cognitively and psychologically costly to frequently revisit and continuously recalibrate their optimal consumption and investment plans. Even minor informational costs can lead investors to prefer infrequent portfolio reviews and adjustments, reinforcing the appeal of fixed or automated saving rules that minimize cognitive effort (Abel, Eberly, and Panageas, 2007, 2013). Third, and importantly, individuals may value flexibility due to unforeseen changes in their tastes, preferences, or personal circumstances. This desire for flexibility introduces a fundamental trade-off between commitment—which protects against short-run temptations and overspending—and flexibility, which allows adaptation to newly available and valuable information. In their theoretical framework, Amador, Werning, and Angeletos (2006) explicitly model this trade-off in a consumption-savings context. They demonstrate that the

optimal design of commitment devices balances these opposing considerations by constraining certain future choices while preserving sufficient flexibility. They find that simple, practical rules such as minimum-savings requirements generally outperform more complex or rigid arrangements because they effectively address temptation without entirely sacrificing the option to adapt to future shocks or preference shifts.

Our empirical setting provides a unique laboratory to examine individuals' revealed preferences for saving rules, capturing their willingness to accept reduced flexibility and optimality in return for psychological relief from mental effort, a reduction in self-control failures, and a balance between commitment and adaptability.

Panel A.1 of Table 2 shows that 41% of the App users choose to set rules. Within this group, the average investor sets 2.55 rules across 1.6 types of rules, with some users setting as many as eight rules across four different rule types.

Panel A.2 shows that individuals who set saving rules automate a significant portion of their deposits, with an average of 73% of their contributions occurring automatically (€1,764 of the total €2,578 deposited). The median user automates 84% of their contributions, and 25% of the investors automate all their contributions.

Panels B.1 and B.2 disaggregate rules' usage by type. The most popular saving rule is MONTH, which is used by 86% of the rule adopters (as shown in Panel B.1) and accounts for 85% of the automated deposits from those who use it (as shown in Panel B.2), in line with existing literature showing that individuals monitor and manage their budgets on a monthly basis (Browning, Crossley, and Joachim, 2014). WEEK, DATE, FIT, and SPORT are equally widespread, with an adoption rate ranging between 14% and 18%. When used, WEEK accounts for 62% of automated users' deposits, meaning that investors use it as a primary saving rule. DATE, FIT, and SPORT account instead between 20% and 32% of investors' automated deposits and are instead secondary saving rules, suggesting that at least some people are willing to associate saving with emotionally rewarding events like the winning of their sports team, their birthday, or their fitness achievements (Loewenstein, Lerner et al., 2003). Finally, DAILY is adopted by only 8% of the users who, however, use it for 46% of their automated deposits.

The results in Table 2 show that users adopt more than one rule at a time, but analyze rule characteristics individually. To understand whether users view different types of rules as complements or substitutes, Figure 1 presents the joint distribution of rule adoption. In particular, each row conditions on users who have adopted a particular rule (i.e., MONTH, WEEK, DAILY, DATE, FIT, and SPORT) and calculates the fraction of users who adopt that rule in conjunction with the rule of the corresponding column. In other words, the diagonal entries in each row present the percentage of users who adopt a specific rule "alone," i.e., without combining it with any other rule. In contrast, off-diagonal entries illustrate the prevalence of combining one rule with another. Since users may adopt more than one rule and the rules are not mutually exclusive, the sum of the entries in each row may exceed 100%.

For example, the first row of the figure shows that 63.5% of the users who adopt MONTH use it alone, 12.6% use MONTH and WEEK together, 5.5% use MONTH and DAILY together, and so on. These results show that the vast majority of users who use MONTH do not choose to add other nonstochastic rules (WEEK, DAILY, and DATE) or stochastic rules (FIT and SPORT).

For all the other rules, we find the opposite pattern, that is, the diagonal entries are always smaller than the off-diagonal entries that involve MONTH. The most extreme cases in this respect are DATE, FIT, and SPORT, which are used in conjunction with MONTH for 84.8%, 81%, and 79.7% of the users, respectively. This suggests that such rules are considered auxiliary and not core rules.

3.2 Design of Rules

Building on the earlier finding that monthly saving rules are the most widely adopted, we now turn to examine how users trade off between different features of saving rules when multiple options are available. The central trade-off lies between the intensive margin (the amount saved per deposit) and the extensive margin (the frequency of deposits). Intuitively, if users adopt more frequent rules (e.g., daily) but reduce the amount deposited each time, total savings may be lower than those associated with a rule that saves less frequently (e.g., monthly), even though the latter involves fewer deposits. Conversely, if deposit amounts decline less than proportionally with increased frequency, a daily rule could generate higher total savings than a monthly one. Previous research (Hershfield, Shu,

and Benartzi, 2020) shows that framing deposits in daily amounts, as opposed to monthly amounts, increases the number of consumers who enroll in saving programs. Our setting instead allows us to study investors' choices when given a variety of options to select from.

To study the relationship between the intensive and extensive margins, it is important to define a window over which the overall savings are computed and to avoid right-censoring bias that can arise from considering the rules established in the latter part of the sample. Therefore, we limit the sample to rules that can be observed for at least one full year, discarding those created in the final twelve months of the dataset. We then examine all deposits linked to each rule up to the one-year mark. This ensures we can accurately compare the within-one-year savings outcomes across different rules (daily, weekly, and monthly).

Figure 2 summarizes our main findings. The top-left panel shows that the distribution of rules across different types is in line with the one in Panel B.1 of Table 2. The top-right panel compares the total amounts saved under different rules. Rules tied to shorter intervals result in slightly higher savings—with overall average savings that equal €556.3 and €516 for daily and weekly rules, compared to €497.5 for the monthly rules. DATE, FIT, and SPORT result in significantly lower savings—€41, €260, and €162, respectively—which is consistent with Figure 1, i.e., that investors regard these as auxiliary rather than core rules.

The bottom panels then decompose these effects further into the number of transactions and the amount per transaction, respectively. The bottom-left panel illustrates that monthly rules tend to remain open longer on average ($8.9/12 = 75\%$ of the year) compared to weekly rules (active for $34.1/52 = 66\%$ of the year) and daily rules (active for $154.2/364 = 42\%$ of the year). The bottom-right panel shows instead that the average Euro per transaction decreases with the frequency of deposits, but it does so less than proportionately. The average deposit for the monthly frequency equals €58.5, which would correspond to average deposits equal to 58.5/4.34=€13.48 and 58.5/30.4=€1.92 at the weekly and daily frequency, respectively. We find instead that weekly deposits average €16.8 and daily deposits average €6.1.

Overall, we find that daily rules, though less popular, result in higher savings compared to weekly and monthly rules. This is despite users tending to close them more often, which suggests that

investors may overestimate their ability to save when establishing daily rules.

3.3 Rules and Fund Type

A crucial dimension of saving rules is their interaction with the characteristics of the investment funds selected by investors. Rules can be especially beneficial when applied to more volatile, equity-based funds, where the potential damage from poor market timing is particularly pronounced. If investors recognize this, we would expect to see a higher prevalence of rules in riskier funds. However, these funds tend to attract less risk-averse individuals—those more inclined to engage in active market timing and less inclined to adopt self-binding constraints. As a result, the very investors who stand to gain the most from automated saving rules may be the least likely to use them.

Moreover, the timing of rule adoption and cancellation may further undermine their effectiveness. If investors tend to create rules after sustained market rallies—precisely when equities are more likely to be overvalued—and cancel them following prolonged downturns, when valuations are more attractive, they risk not only forfeiting the benefits of disciplined investing but also reinforcing the very behaviors that saving rules are designed to curb.

We begin by reporting in Figure 3 the percentage of users who adopt a saving rule, conditional on their investment type: equity, balanced, or fixed-income funds. Adoption rates are 49% for equity investors, 46% for balanced, and 42% for fixed-income. Statistically, these values are all different from each other. From an economic perspective, rule adoption is 17% higher among equity investors compared to fixed-income investors, and 6.5% higher than among balanced investors. This pattern is consistent with the idea that investors are more likely to implement rules when investing in riskier, more volatile funds, where poor market timing can be especially costly.

Table 3 focuses on the timing of rule creation and deletion. We estimate the following regression model:

$$\begin{aligned}\mathbb{1}\{Rule\}_{i,j,t} = \alpha_i + \alpha_t + \beta_1\ Ret_{j,[-1,-7]} + \beta_2\ Ret_{j,[-8,-30]} \\ + \beta_2\ Ret_{j,[-31,-60]} + \beta_3\ Ret_{j,[-61,-180]} + \beta_4\ Ret_{j,[-181,-360]} + \epsilon_{i,j,t}\end{aligned} \tag{1}$$

where $\mathbb{1}\{Rule\}_{i,j}$ is a dummy variable equal to 1 if user i has created (in Panel A) or deleted (in Panel

B) a rule in fund j at time t; α_i and α_t denote user and time fixed-effect. To avoid multicollinearity issues induced by including returns computed over overlapping windows, we use the return of the fund over the previous week ($Ret_{j,[-1,-7]}$), the previous month excluding the previous week ($Ret_{j,[-8,-30]}$), the previous three months excluding the previous month ($Ret_{j,[-31,-60]}$), the previous six months excluding the previous three months ($Ret_{j,[-61,-180]}$), and the previous year excluding the previous six months ($Ret_{j,[-181,-360]}$).

Column 1 of Panel A focuses on all rules and shows that investors are more likely to create a rule after experiencing positive returns (up to six months). In columns 2, 3, and 4, we estimate our baseline regression conditioning on the type of fund and find that the effect is strong for Equity funds but weaker and more sparse for balanced and fixed-income funds, suggesting that only substantial variation in returns affects rule creation systematically.

In Panel B, we repeat our analysis for rule deletion. The first column reveals a negative relationship, indicating that negative returns coincide with rule deletions in a manner that mirrors the pattern observed for rule creation. When we condition by fund type in columns 2, 3, and 4, we find that the result is strong for equity funds but insignificant for balanced and fixed-income funds, similar to what we observe for rule creation.

Overall, our findings indicate that investors are somewhat susceptible to recent market returns when creating or canceling saving rules. This highlights a potential need for financial education or alternative nudges to reduce harmful market-timing behaviors and enhance the overall effectiveness of these rules.

4 Investment Rules And Saving

In this section, we first discuss the economic channels through which automated recurring investment rules could affect saving rates and quantify their economic magnitude (Section 4.1). We then establish that the effect is causal (Section 4.2).

4.1 Reduced Form Results

As mentioned in Section 3.1, saving rules can help individuals overcome biases and frictions that limit their ability to save. However, these effects hinge on how users design their rules. Since users choose the features of the rules on their own, they might do it sub-optimally. For example, they might create rules featuring a periodic deposit that is too high relative to the frequency. Consequently, even if these rules initially generate substantial savings, their effectiveness may diminish rapidly, as users are likely to abandon overly burdensome rules that strain their budgets. At the other end of the spectrum, rules featuring deposits too small relative to the frequency might have a negligible overall economic effect on users' savings. As discussed in Section 3, creating a rule entails balancing the tradeoff between the cost of making periodic decisions and the cost of losing such flexibility. Since once initiated, automated rules go on indefinitely, particularly risk-averse users might decide to set saving rules that are too conservative.

Second, automated rules may influence savings through their indirect effect on manual deposits. Specifically, once users set up automated deposits, they might become less engaged with the app and reduce either the frequency or size of their manual deposits. If the automated deposits do not fully offset this crowding-out effect, overall savings could decrease rather than increase. Conversely, some automated rules—particularly those with a stochastic or emotional component, such as linking savings to sports outcomes, birthdays, or personal physical achievements—may enhance user engagement and ultimately encourage more frequent manual deposits (Blanchard and Palazzolo, 2024).

To quantify which of these channels dominate, we estimate the following panel regressions:

$$Y_{i,t} = +\beta \mathbb{1}\{Rule\}_{i,t} + a_i + \tau_t + \epsilon_{i,t}, \tag{2}$$

where $Y_{i,t}$ is either the deposits, withdrawals, or net-savings (i.e., the difference between the two) of user i in month t, $\mathbb{1}\{Rule\}_{i,t}$ is a dummy variable equal to 1 if user i has an active rule (i.e., a rule triggering a transaction) in month t, while a_i and τ_t denote user and time fixed-effects. The coefficient of interest is β, which captures the difference in the dependent variable when users have a rule activated compared to when they do not, controlling for time-invariant factors across users and time-varying factors common to all users. To capture the degree of substitution between manual and

rule-based transactions, we estimate the effect separately for automated and manual transactions.

The results in the first column of Panel A in Table 4 show that rules are associated with an increase in total deposits by €87.74, which is significant at the one percent level (t-stat of 35.59). The effect is also economically significant since the average deposit when a rule is not active is €26.54. When using manual deposits, we estimate a coefficient of €−2.95 (with a t-stat of −2.23), indicating that there is very little substitution effect between manual and automated deposits. Economically, since the average deposit when a rule is not active is €26.54, it corresponds to a drop of 11%.[21] The estimate in the third column, which is only based on recurring transactions, confirms that the increase in total deposits is mostly driven by rules, as the average rule-based deposit is €90.69, statistically significant at the one percent level (t-stat of 43.37)

Pane B displays the results for withdrawals. Since withdrawals can only be performed manually, the coefficient estimates in the first two columns are the same, and indicate that rules have a positive effect on saving also through a reduction in withdrawals. More specifically, when rules are active, withdrawals decline by €14.68 (with a t-stat equal to −8.94). Panel C reports the results for net savings. Given the increase of €87.74 in total deposits from Panel A and the decline of €14.68 in withdrawals from Panel B, we estimate an effect of €102.42 in total net savings when a rule is active. This net savings increase can also be decomposed into automated savings of €90.69 and a smaller increase in manual net savings of €11.73, driven primarily by the lower withdrawal rate.

A natural concern with the results in Table 4 is that users might "test" the App with a few small manual transactions and then immediately start a rule, thus generating a large economic difference between the months when a rule is active and months when it is not. To assess the relevance of this concern, we re-estimate the effect on total deposits, withdrawals, or net savings only for those users who have made a manual deposit for at least 2, 4, or 6 months. Results are reported in Appendix Table A.1. Panel A, focusing on deposits, shows that the estimated β coefficients remain similar to baseline results (we estimate €87.74 in column 1 in Panel A of Table 4), ranging from €91.01 to €96.11, regardless of how long users made manual deposits before initiating a rule. However, average manual deposits increase as we condition the regressions, rising from €26.54 in the baseline to €49.62,

[21] Note that the average deposit when a rule is not active is mechanically the same as column *Total* because in these instances total deposits are made only by manual deposits.

€60.29, and €65.34 across columns 1 to 3, implying that the incremental effect of recurring savings rules diminishes for these groups. Nevertheless, even for users in the latter category, the impact remains economically significant, representing a 47% (i.e., 96.11/65.34 - 1) increase in savings.

4.2 Identification Strategy

The results in the previous section have the benefit of being computed for a large cross-section of users and over a relatively long sample of four years featuring different market conditions. However, they cannot be interpreted causally because the decision to create a rule is endogenous and might be driven by individual-level time-varying factors not controllable for in Equation 2 and correlated with a user propensity to save.

To this end, we designed a Randomized Encouragement experiment. This design has been used in a variety of settings ranging from social sciences to medicine (see, e.g., Duflo and Saez, 2003, West et al., 2008, Mullally, Boucher, and Carter, 2013, Eckles, Kizilcec, and Bakshy, 2016 and Fowlie, Greenstone, and Wolfram, 2018) and is common when access to the treatment cannot be offered only to a subset of individuals or is already available and cannot be denied.[22] In a standard encouragement design, all subjects have access to the treatment, but some (the encouraged group) are randomly assigned to receive encouragement (i.e., external stimulus or incentive) to take it. Thus, the aim of the encouragement is to increase the likelihood of adoption without forcing it. Common forms of encouragement include financial incentives (such as vouchers and cash rewards, see e.g., Katz, Kling, and Liebman (2001)) and informational nudges (such as emails and notifications, see e.g., Fowlie, Greenstone, and Wolfram, 2018 and Duflo and Saez, 2003). The encouragement is then used as an Instrumental Variable for the endogenous decision to adopt the treatment. Imbens and Angrist (1994) and Angrist, Imbens, and Rubin (1996) show that this design allows for the estimation of the local average treatment effect (LATE), i.e., the effect of the treatment for the compliers, as long as the exogeneity, relevance, exclusion restrictions, and monotonicity assumptions of the instrument are satisfied.

In our protocol, on each day between September 2024 and December 2024, a random fraction of all

[22] We use this approach because our data covers a period when all users had access to recurring rules, and the company could not deactivate the feature only for some for regulatory and ethical reasons.

new users (i.e., users who created a profile on the app) were assigned to an encouraged group receiving notifications from the marketing team highlighting the benefits of recurring rules, while the control users did not receive any notification on rules. The notifications highlighted several key benefits of automated rules, such as the advantages of automation in reducing the cognitive costs of making decisions, the flexibility in choosing the deposit frequency, and the possibility of personalizing rules to individuals' characteristics. We use these notifications as an instrumental variable, allowing us to isolate the portion of rule adoption that is uncorrelated with users' innate saving tendencies and thus estimate the causal impact of automated rules on saving behavior.

In our setting, the exogeneity of the instrument is satisfied by the randomness of the assignment. While exclusion restrictions are ultimately untestable, the notification only highlighted the benefits of rules rather than savings in general. Moreover, we test whether users targeted by the notification who did not create a rule also display a positive change in savings. To assess the relevance of the instrument, we obtain the following estimates from the first-stage cross-sectional regression:

$$\begin{array}{lll} \mathbb{1}\{Rule\}_i = \underset{(8.48)}{0.154} + \underset{(3.27)}{0.149} \times \mathbb{1}\{Encouraged\}_i + \epsilon_i, & & R^2 = 0.024, \\ & & F - stat = 10.7 \end{array}$$

where $\mathbb{1}\{Rule\}$ denotes a dummy variable equal to one if user i has created a rule and zero otherwise while $\mathbb{1}\{Encouraged\}$ denotes a dummy variable equal to one if user i belongs to the encouraged set of users. The coefficient of interest is the one associated with $\mathbb{1}\{Encouraged\}$, which captures the difference in adoption rate between the encouraged and the control group. We find an estimate of 0.149, with an associated t-statistic 3.27, which indicates that the users who received the notification about the rules have a 14.9% higher probability of creating a rule. Considering that the constant is 15.4%, our results suggest that encouragement is very effective in increasing rule creation among our users. To assess whether our instrument is weak, we examine the Kleibergen-Paap (KP) Wald F-statistic, which is 10.7—exceeding the commonly suggested threshold of 10 and indicating that weak instrument concerns are unlikely.

In Columns (1) and (2) of Table 5, we report results from OLS and the following second-stage

regression:

$$Y_i = \alpha + \beta \widehat{\mathbb{1}\{Rule\}}_i + \epsilon_i$$

where $Y_{i,t}$ denotes average daily deposits, withdrawal and net-saving of user i, and $\widehat{\mathbb{1}\{Rule\}}$ denotes a dummy variable equal to one if user i has created a rule instrumented by $\mathbb{1}\{Encouraged\}_i$, a dummy if the user was targeted by the notification. We use daily averages rather than total quantities because subjects enter at different points in time during the experiment, and those who enter at the beginning (i.e., on the first days of September 2024) would mechanically display higher deposits. The coefficient of interest is β, which captures the local average treatment effect (LATE), i.e., the causal effect of the automated rules on saving for the compliers (i.e., the rule adopters).

Starting from deposits, displayed in Panel A, the OLS estimates are in line with those reported in Table 4 and indicate that users who do not adopt rules save €1.199×30=€35.97 per month, while rule-adopters save €3.770×30=€113.1 more, which is strongly statistically significant (t-stat equal to 6.65). We obtain an IV estimate of €9.865, with a t-stat of 2.55, indicating that rules have a causal effect on savings. The corresponding results in Panels B and C show the results for withdrawal and net savings, and show that the changes in net savings are almost entirely driven by the increase in deposits rather than any sizable change in withdrawals.

From a policy perspective, one could be interested in the Intent-To-Treat (ITT) estimate, which is instead the causal effect of receiving a random notification regarding the automated recurring rules, irrespective of whether the user ultimately adopts them. More formally, we estimate the following regression:

$$Net\_Saving_i = \alpha + \beta \mathbb{1}\{Encouraged_i\} + \epsilon_i$$

The results, reported in column 3, indicate that the encouragement increased deposits by €1.468 per day, thus encouraged users realized average daily deposits equal to €1.468+€1.567=€3.035.

Taken together, the results of this section indicate that automated rules have an economically sizable causal effect on net-saving rates, primarily driven by increased deposit rates among users who

adopt these rules.

5 Rules And The Gap Between Users and Fund Returns

A recent study from Morningstar on the US market indicates that retail investors lost out on about 15% of the return their mutual funds and ETFs generated because of the timing of their purchases and sales of fund shares (Morningstar (2024)). By automating the purchasing decisions, recurring investment rules have the potential to discipline investors' flow and reduce their sensitivity to past performance. Unless this effect is undone by their sales decision, recurring investment rules can better align investors' performance with those of the funds they invest in.

In this section, we discuss the relation between recurring investment rules and dollar-cost averaging (Section 5.1) and provide results on how automated rules eliminate trend-chasing behavior (Section 5.2) and reduce the gap between investors' and funds' returns (Section 5.3).

5.1 Recurring Rules and Dollar-cost Averaging

Unless investors follow a buy-and-hold strategy over the entire period, the returns they realize will generally differ from the returns of the underlying funds. The timing of the deposits and withdrawals drives the wedge between the two. Intuitively, if an investor deposits a larger fraction of their total investment before the asset appreciates (depreciates), their return will be higher (lower). Dollar-weighted returns measure an investor's return from an asset over a given period based on their pattern of deposits and withdrawals.

Extensive evidence shows that retail investors display trend-chasing behavior when investing in mutual funds, both in the time series and cross-section (Choi et al., 2009; Tran and Wang, 2023; Bailey, Kumar, and Ng, 2011; Choi and Robertson, 2020a). Funds that have experienced positive past performance receive positive inflows, while those underperforming experience redemptions. This tendency arises from extrapolative expectations, i.e., the fact that investors interpret past positive performance as a predictor of future performance. Since mutual fund performance displays little persistence, trend-chasing typically leads to lower returns than those realized by the fund (Bollen and Busse, 2004; Busse, Goyal, and Wahal, 2014). Moreover, the positive feedback between past performance and flows is dis-

ruptive to mutual fund managers who experience redemptions after underperformance, forcing them to sell assets to meet liquidity demands (Coval and Stafford, 2007b). Automated investments could have stabilizing implications for mutual fund managers.

Activating automated saving rules is a simple way for investors to implement a "dollar-cost averaging" strategy. The price of ETFs and shares fluctuates as markets rise and fall, meaning the investments are purchased at different prices because they are bought at different times. This is beneficial because fewer shares are purchased when prices are high, and more are acquired when prices are low. Overall, this strategy tends to lower the average entry cost into specific assets over time. While reducing the cost of investing is a positive aspect, the most significant advantage of dollar-cost averaging is that it promotes discipline and mitigates behavioral biases or emotional factors in investing decisions, such as trend-chasing.

5.2 Trend Chasing with Manual and Automated Transactions

As a first exercise, we study whether individuals who engage in manual and automated deposits display trend-chasing behavior. In Table 6, we report the estimate from the following regression specification:

$$\begin{aligned} Deposit_{i,j,t} = \beta_1 Ret_{j,[-1,-7]} + \beta_2 Ret_{j,[-8,-30]} + \beta_2 Ret_{j,[-31,-60]} \\ + \beta_3 Ret_{j,[-61,-180]} + \beta_4 Ret_{j,[-181,-360]} + \alpha_i + \alpha_t + \epsilon_{i,j,t} \end{aligned} \tag{3}$$

where $Deposit_{i,j,t}$ denotes the (logged) deposits of user i in fund j on day t, $Ret_{j,[-t_1,-t_2]}$ denote returns of fund j in between the t_1 and t_2 prior days. To avoid multi-collinearity issues, we resort to non-overlapping returns at different horizons. α_i and α_t denote user and time fixed-effect.

Panel A reports the results across all funds and splits the results across manual and recurring deposits in the first and second columns, respectively. The manual deposit results show that investors' deposits are very sensitive to mutual fund's past performance, with the coefficients remaining statistically and economically significant for returns at all horizons. The economic magnitude of the coefficients remains roughly unchanged up to the six-month horizon. Since longer-term returns have higher standard deviations, this indicates that the investors' sensitivity peaks at horizons between three and six months. The coefficient estimates for the recurring investments, on the other hand,

show that there is no relation between mutual fund returns and deposits, and that recurring investments eliminate investors' market timing.

Panels B, C, and D repeat the results for equity, balanced, and fixed-income funds, respectively. For manual deposits, the coefficient estimates show significant trend-chasing for equity funds, with a sensitivity that peaks between three and six months. We also detect trend-chasing at horizons of less than one month in balanced funds, but no trend-chasing in fixed-income funds. Across all fund types, we find instead no relation between recurring deposits and fund returns.

Overall, the results in this section suggest that individual investors exhibit significant trend-chasing behavior when making manual deposits, and recurring investments effectively eliminate this tendency.

5.3 The Gap Between Investor Returns and Fund Performance

If investors exhibit poor market timing behavior—potentially due to trend-chasing, as discussed in Section 5.2—we would expect a discrepancy between the performance of the mutual funds they invest in and the actual returns they realize. To analyze this relationship, first calculate the "return gap" for each investor in each fund, which is computed as the difference between the dollar-weighted returns that the investors achieve and the returns of the fund over the same period. The dollar-weighted returns are calculated using the standard Internal Rate of Return (IRR) formula:

$$\sum_{t=0}^{T} \frac{C_t}{(1+IRR)^t} = 0.$$

C_t represents the cash flow at time t, where investments are negative, and withdrawals are positive; IRR denotes the Internal Rate of Return, which is the discount rate that makes the net present value (NPV) of all cash flows equal to zero. The variable t corresponds to the time period in years, and T represents the total number of years considered in the calculation, which is either when the investor closes their positions in the fund or the end of the dataset.

We then estimate the following regression specification:

$$Return\_Gap_{i,j} = \alpha + \beta \ \ \%Rule_{i,j} + \epsilon_{i,j},$$

where $Return\_Gap_{i,j}$ denotes the difference between the dollar-weighted return of user i in fund j and the return of fund j over the same period; $\%Rule_{i,j}$ denotes the fraction of deposits made with a Rule by user i in fund j.

In Panel A of Table 7, we report the results for all funds. The first column shows that the average investor trails the performance of the funds they invest in by 1.62% per year, i.e., they have a negative return gap. The coefficient on $\%Rule_{i,j}$ is 0.99, showing that investors who automate 100% of their deposit close their gap by 61%. Because trend-chasing and other behavioral tendencies may be more or less pronounced and detrimental depending on the performance of the funds they invest in, in the second column, we repeat the analysis for funds that generated positive returns during the investor's holding period. When depositing manually, investors experienced a negative returns gap of 1.37%, and recurring rules closed such a gap by 0.58%. The third column focuses instead on funds that generated negative returns during the investor's holding period. For this group, the (negative) returns gap was much larger, at -1.94%, and the use of the recurring rule has a particularly strong effect in closing the gap, as the coefficient on $\%Rule_{i,j}$ equals 1.59%, entailing that investors who use rules close their gap by 82%.

In Panel B, we condition the analysis on the type of fund. The first column starts with Equity funds and shows that the return gap equals -1.44%, and the use of rules closes the gap by 0.47/1.44=33%. The second column focuses on Balanced funds and shows that the return gap is similar at -1.72%, and the use of rules is slightly less effective, closing the gap by 0.63/1.72=37%. Finally, Fixed-Income funds are where we find a larger return gap that equals -1.61%, and the use of rules more than closes the gap. The coefficient on $\%Rule_{i,j}$ equals 1.69%, suggesting that investors who make 100% of the deposits using rules outperform the funds they invest in by -1.61%+1.69%=0.08%.

The results reported in Table 7 show the differential degree of effectiveness of recurring investments in narrowing the gap between the returns realized by the funds and the investors over a given period. A notable aspect of the results, especially the ones reported for all funds in the first column of Panel A, is that they imply that even those who automate 100% of their investments lag the funds' returns by 63 basis points. While we may not expect the return gap to be zero even for those who use recurring investments because the returns of the funds represent those of a lump-sum investment

at the beginning of the investment period, there could also exist a nonlinear relation between the return gap and the percentage of recurring investments. To assess whether this second channel plays a role, we re-estimate the relation between the two quantities using a symmetric nearest neighbor smoothing procedure. The results, reported in the top panel of Figure 4, show that, indeed, there is an exponential relation between the two variables, with those automating 0% of their deposits having returns that lag those of the funds they invest in by 1.5%, and those that automate 100% of their deposits experiencing a return gap of 0%.

A second potential limitation of the results in Table 7 is that they estimate the effect of recurring rules on the mean of the distribution, while their effect on the return gap might be heterogeneous depending on how well the investors time the market when making discretionary deposits. To this end, the lower panel of Figure 4 displays the density distributions of the return gap separately for users who automate more than 50% of their transactions (red line) and those who automate less than 50% (blue line). Overall, we find that the whole distribution of those who automate more than 50% of their deposits stochastically dominates the one of those who don't, but the bulk of the effect seems to be concentrated in the right tail of the distribution.

Overall, these results show that automating deposits has a significant effect on allowing investors to narrow—and in some cases close—the gap between the returns they realize and the performance of the funds they invest in.

6 Economic Drivers of Rule Adoption: Survey Evidence

The results in the previous sections indicate that automated investment rules have a positive impact on adopters' financial well-being. First, they increase saving rates by promoting more regular deposits without crowding out manual contributions. Second, they improve investment performance through the benefits of dollar-cost averaging. In this section, we examine the motivations and beliefs associated with the adoption of automated savings rules, based on the survey design presented in Section 2.2. Understanding these behavioral patterns is essential for designing effective interventions to encourage broader adoption and, ultimately, enhance long-term financial welfare.

We first analyze respondents' answers to a structured set of Likert-scale questions, comparing

average ratings across different motives for both adopters and non-adopters (Section 6.1). We then complement this analysis with open-ended responses, which we process using a keyword-based topic classification approach (Section 6.2). Finally, we examine how beliefs about market timing and investment behavior correlate with the likelihood of using automated rules (Section 6.3).

6.1 Motives for Adopting Rules: Closed-ended Questions

The closed-ended survey questions were designed to identify the core psychological and economic mechanisms that motivate or deter the adoption of recurring savings rules, drawing on insights from the existing economic and psychology literatures.

We asked respondents who had created a rule to rate the importance of six specific motives: (i) *help avoid procrastinating on saving*, reflecting self-control and present-bias concerns (Laibson, 1997; Ashraf, Karlan, and Yin, 2006; O'Donoghue and Rabin, 1999); (ii) *save time by reducing the need to monitor the markets*, aligned with attention constraints (DellaVigna and Pollet, 2009; Abel, Eberly, and Panageas, 2007, 2013); (iii) *eliminate the stress and mental burden of making decisions each time*, highlighting cognitive load and decision fatigue (Bertrand, Mullainathan, and Shafir, 2004; Shah, Mullainathan, and Shafir, 2012; Kahneman, 2011); (iv) *are fun and motivating* (Thaler and Benartzi, 2004a; Karlan et al., 2016); (v) *take advantage of volatility to lower the average purchase price (dollar-cost averaging)* (Statman, 1995); and (vi) *avoid the temptation to time the market*, related to overconfidence and market timing biases (Shefrin and Statman, 1985; Barber and Odean, 2001).

The top-left panel of Figure 5 presents the average Likert-scale ratings for each motive together with 95% confidence intervals. Respondents evaluated each motive on a scale from 1 ("not important at all") to 5 ("very important"). Given the ordinal nature of the data, we use a Wilcoxon rank-sum test to assess whether each motive's mean rating differs significantly from 3, corresponding to a neutral stance. The full distribution of responses is shown in the bottom-left panel of Figure 5, and pairwise comparisons across all motive combinations are reported in Panel A of Table 8.

Among adopters, three motives emerge as clearly dominant: *avoiding procrastination*, *overcoming limited attention*, and *reducing the stress and effort of decision-making*. Each of these motives receives average ratings above 3.9, with more than 75% of respondents assigning them a score of 4 or 5 (bottom-

left panel of Figure 5). In contrast, motives more closely related to investment optimization—such as *increasing motivation*, *engaging in dollar-cost averaging*, and *avoiding market timing temptation*—receive more modest support, with average ratings in the 3.2–3.4 range and a larger proportion of neutral or low ratings in the bottom-left panel of Figure 5.

The pairwise comparisons reported in Panel A of Table 8 reveal a clear ranking among motives. *Avoiding procrastination* is rated significantly higher than every other motive, with all pairwise differences statistically significant. *Overcoming limited attention* ranks second, outperforming all motives except *voiding procrastination*. *Reducing stress and effort* is rated significantly higher than all but the top two. In contrast, *increasing motivation* is rated significantly higher than only *dollar-cost averaging* and *the temptation to time the market*. The bottom two motives—*dollar-cost averaging* and *timing temptation*—are statistically indistinguishable from each other. These findings underscore that automation is especially attractive to individuals seeking to overcome behavioral frictions—such as inertia, limited attention, and decision fatigue—rather than as a tool for optimizing portfolio performance and reducing the temptation to time the market.

Understanding why individuals choose *not* to adopt recurring savings rules is especially important from a welfare perspective. Some barriers, like a lack of understanding, can be addressed through improved rule design, framing, and communication, enabling a broader range of individuals to benefit from commitment mechanisms. Others—such as liquidity constraints or income instability—reflect deeper financial vulnerabilities that can render automated saving unfeasible, regardless of how the rules are structured or presented.

To this end, we asked respondents who had not created a rule to rate the importance of seven specific motives: (i) *I don't know how to create the best rule for me*, reflecting optimization frictions and perceived decision complexity (Carroll et al., 2009); (ii) *I'm already disciplined and invest regularly*, reflecting an internal sense of financial control and self-efficacy (Van Rooij, Lusardi, and Alessie, 2011); (iii) *I want to decide how much to save based on circumstances*, reflecting a preference for flexibility and state-contingent decision-making (Gul and Pesendorfer, 2004); (iv) *My income is too variable*, reflecting liquidity risk and precautionary savings motives (Carroll, 1997; Dynan, Skinner, and Zeldes, 2004); (v) *I don't have money to save*, reflecting resource scarcity and binding liquidity

constraints (Kaplan, Violante, and Weidner, 2014); (vi) *I don't understand how it works*, reflecting cognitive barriers and financial complexity (Campbell, 2006), and (vii) *I don't know what a savings rule is*, reflecting limited attention and lack of salience.

The top-right Panel of Figure 5 and Panel B of Table 8 present the corresponding results. The preference for *flexibility* (mean = 4.12) stands out as the most important motive among non-adopters. It is followed by *already disciplined* (3.66) and *income volatility* (3.48), all of which are rated significantly above the neutral benchmark, with a majority of respondents assigning them scores of 4 or 5. Notably, one informational barrier—*not knowing how to set a rule*—also receives a moderately high score (mean = 3.44), suggesting that decision complexity plays a role for a subset of users. In contrast, other informational frictions—*not understanding how it works* and *being unaware of the feature*—receive lower ratings (means between 3.17 and 3.30), with most responses in the 1–3 range. Finally, *not having enough savings* receives the lowest score (mean = 3.01), which is statistically indistinguishable from the neutral score of 3. These results indicate that while decision complexity is relevant for some, the primary obstacles to adoption lie in structural factors such as income instability and a preference for flexibility over automation.

The pairwise tests support this interpretation. *Flexibility* is rated significantly higher than every other alternative. *Already disciplined* ranks second, beating three of the six remaining motives. *Income volatility* and *not knowing how to set a rule* come next, with statistically indistinguishable ratings, each outperforming two of the remaining alternatives. From a policy perspective, our results indicate that increasing adoption may require more than informational nudges; it may require addressing structural barriers and embedding greater flexibility into the design of recurring savings rules.

6.2 Motives for Adopting Rules: Open-ended Questions

Following the approach of Stantcheva (2023), Haaland, Roth, and Wohlfart (2025) and Bergman et al. (2020), we complement our structured survey analysis with two open-ended questions aimed at eliciting respondents' motivations and barriers in their own words, unprompted by predefined motives. These questions were presented early in the survey to minimize framing effects.

Respondents who had set a rule were asked: "*Why did you decide to create a recurring savings*

rule?" Those who had not were asked: "*Why have you not created a recurring savings rule?*" We process these free-text responses using a keyword-based classification strategy. After cleaning and standardizing the text, we assign each response to one or more thematic categories using curated dictionaries of semantically related terms.[23]

The left panel of Figure A.2 summarizes the most frequent themes among adopters. Three motives dominate: *Stress and Effort* (with 39.9% of adopters mentioning it), *Procrastination* (25.9%), and *Limited Attention* (24.7%). These closely mirror the top-rated motives in the closed-ended Likert-scale questions shown in Figure 5, providing strong validation that the multiple choice questions captured the primary psychological drivers of rule adoption. In contrast, investment-oriented themes such as *temptation to time the market* (1.1%) and *dollar-cost averaging* (0.8%) are rarely mentioned—again consistent with the lower average ratings these received in the multiple choice responses. The right panel of Figure A.2 presents results for non-adopters. The most frequently cited reasons are *no need* (32.1%) and *preference for flexibility* (28.6%), followed by informational frictions such as *unawareness* (19.6%) and *lack of understanding* (14.8%). These results echo the Likert-scale responses in the top-right panel of Figure 5, where similar motives emerged as most important. As with adopters, the open responses reveal limited concern with optimization or financial strategy; instead, respondents often view rules as unnecessary or express a preference for retaining flexibility and control.

The fact that the same core behavioral mechanisms emerge across both open- and closed-ended questions suggests that the motives we elicited in the latter format captured the most salient drivers of rule adoption.

[23]For adopters, we isolate the following topics: *Procrastination* comprising the words procrastination, discipline, spend, force, impose, regular, and difficult; *Stress and Effort* comprising the words stress, effort, think, decide, automate, choose, simplify, facilitate, practical, and simple; *Limited Attention* comprising the words forget, remember, time, regular and routine; *Timing Temptation* comprising the words: irrational, human, and sentiment; *Motivating* comprising the words: motivate, stimulate, incentivize, and target; *Dollar costaveraging* casually, price, drop, and increase; *Try* comprising the following word try. For non adopters, we isolate the following topics: *Flexibility* comprising the words flexibility, voluntarily, constraints, and can; *Already disciplined* comprising the words: same and already; *Volatile Income* comprising the word: keep; *Not Know How* comprising the word procedure; *Not Know What* comprising the words: know and ignorance; *No Understand* comprising the words what and clear; *Not enough savings* comprising the words lack, enough and savings; *No need* comprising the words need, not interested, no necessary.

6.3 Beliefs, Demographic Characteristics and Automated Rule Adoption

We conclude this section by examining how individuals' expectations about market timing, beliefs about return predictability, mutual fund selection criteria, and demographic characteristics relate to the adoption of automated savings rules.[24] This analysis helps assess whether rule adoption reflects strategic investment considerations or is instead driven by other behavioral or structural factors.

We estimate cross-sectional regressions of the following form:

$$\mathbb{1}_{Rule\_Adopter_i} = \sum_{k=1}^{K} \mathbb{1}_{\{X_{i,k}=1\}} + \epsilon_i, \tag{4}$$

where $\mathbb{1}_{Rule\_Adopter_i}$ is a dummy equal to one if respondent i has ever adopted a rule. The term $\mathbb{1}_{\{X_{i,k}=1\}}$ is an indicator variable equal to 1 if individual i belongs to demographic group k, with K denoting the total number of mutually exclusive groups for a given characteristic. We estimate these regressions separately for each demographic dimension. Each regression is estimated without a constant, so that the coefficient on each indicator represents the average willingness-to-adopt score for respondents in the corresponding group. We display the results in Figure 6.

Panels (a) and (b) show that neither the extent to which individuals attempt to time the market nor their perceived ability to do so is associated with higher rates of rule adoption. Similarly, Panel (c) indicates that beliefs about return predictability do not significantly explain adoption behavior. These results reinforce the earlier finding in Figure 5 that investors do not view automated savings rules as tools for improving market timing or exploiting predictable returns.

Panel (d) examines the relationship between fund evaluation criteria and rule adoption. Individuals who place greater emphasis on attributes such as fund fees, risk, and manager experience are more likely to adopt automated savings rules. Panels (e) and (f) explore adoption patterns across income and education levels. Adoption rises steeply in the lower part of the income distribution but flattens beyond approximately 3,000 EUR/month. Education is also mildly positively associated with rule adoption. These patterns suggest that adopters tend to be more financially sophisticated—arguably the individuals who need such tools the least. In contrast, those who might benefit most from automation appear less likely to take it up.

[24] Figure A.3 reports the distribution of these variables.

The fact that beliefs about timing and return predictability are not key drivers of adoption—and that adopters tend to be more financially secure and sophisticated—points to two complementary policy recommendations. First, financial education efforts should emphasize that automated savings tools not only help individuals overcome behavioral frictions but also promote consistent investing and reduce harmful market timing attempts. Second, targeted outreach should focus on less financially sophisticated and more vulnerable individuals—those currently least likely to adopt rules but potentially most likely to benefit from the discipline and structure that automation provides.

7 Conclusions

We study how automated investment rules, a feature now introduced by some of the largest U.S. brokerages and other financial institutions, affect saving behavior and investment outcomes using data from a FinTech app designed to help small investors access mutual funds. Users design their own rules and can set deterministic rules for scheduled deposits—monthly, weekly, daily, or on specific dates—or stochastic rules triggered by specific conditions.

Consistent with the notion that automation could appeal to investors who struggle with present bias, limited attention, or self-control, we find that almost half of the app users adopt investment rules. Among rule adopters, the majority rely on more than one rule, automating a large fraction of their deposits.

Using a randomized encouragement design, we provide causal evidence that automated saving rules increase average savings without crowding out manual contributions. We also show that automated rules reduce trend-chasing behavior: while manual deposits respond strongly to recent returns, automated ones do not, narrowing the gap between fund returns and realized investor returns.

These results have important implications for social welfare, particularly in light of recent statistics showing that the majority of U.S. adults lack sufficient savings to withstand income shocks and are unprepared for retirement. Besides the implication for investors' welfare, our central finding that automated rules reduce the feedback between between past performance and investment flows is important because the trading behavior of retail investors might contribute to bubbles (see, e.g., Pearson, Yang, and Zhang (2021)) and is disruptive to mutual fund managers who experience redemptions after

underperformance, forcing them to sell assets to meet liquidity demands (Coval and Stafford, 2007b).

However, rule timing remains sensitive to past performance—users are more likely to adopt rules following periods of strong returns and to suspend them during downturns, particularly in equity funds. This opens several avenues for future research, including understanding which tools are most effective at enhancing the impact of automated rules (such as personalized recommendations or positive reinforcement), identifying strategies to reduce the tendency to delete rules based on poor recent fund performance, and examining how automated rules interact with other behavioral nudges to support better investment outcomes.

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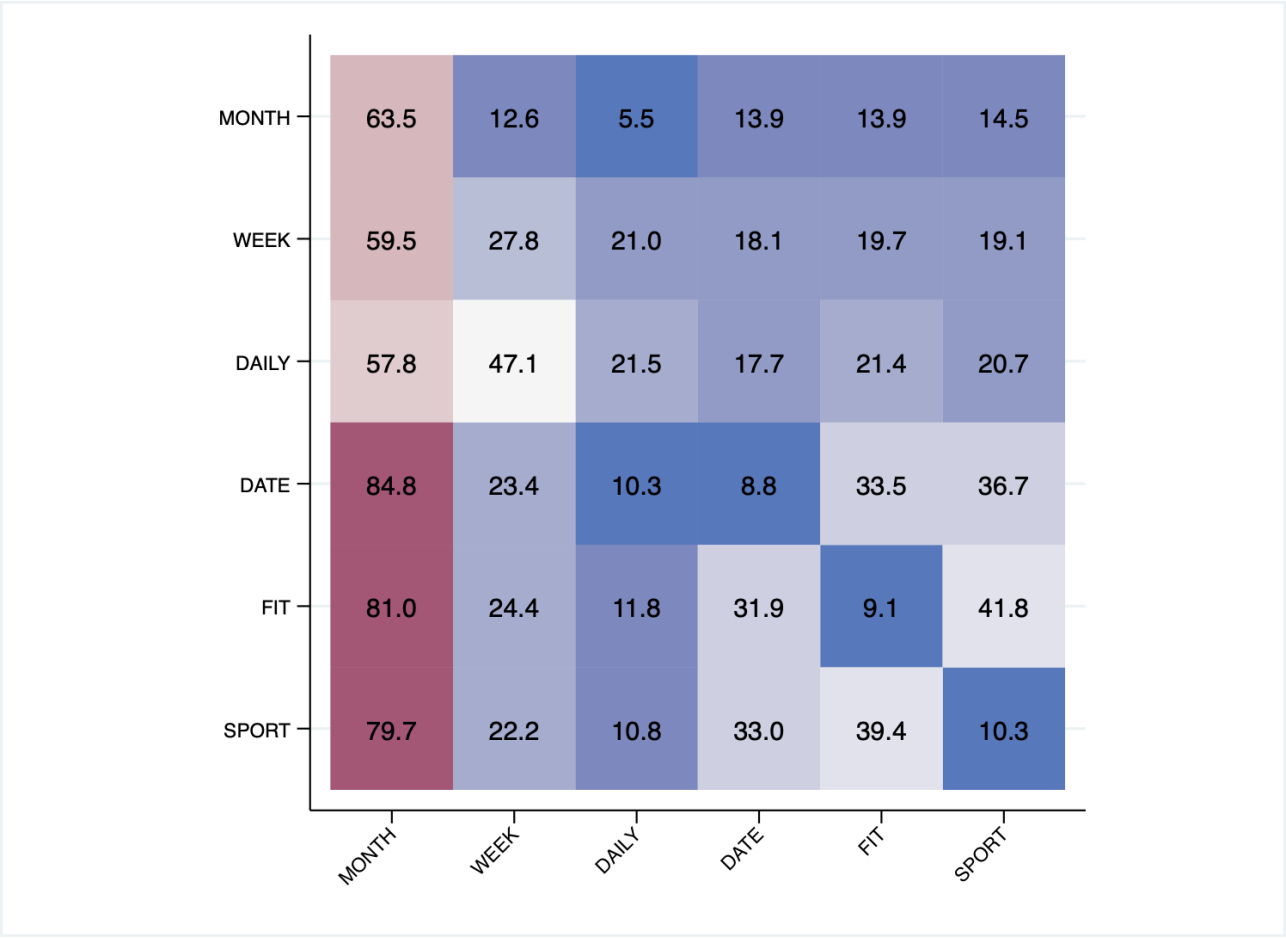


Figure 1: This figure shows the joint probability of rule adoption. Each row represents all users who have adopted a particular rule (i.e., MONTH, WEEK, DAILY, DATE, FIT, and SPORT). We then calculate the fraction of users who adopt that rule alone (diagonal entries in the matrix) or in combination with any other rule (off-diagonal entries). Since users may adopt more than one rule and the rules are not mutually exclusive, the sum of the entries in each row may exceed 100%.

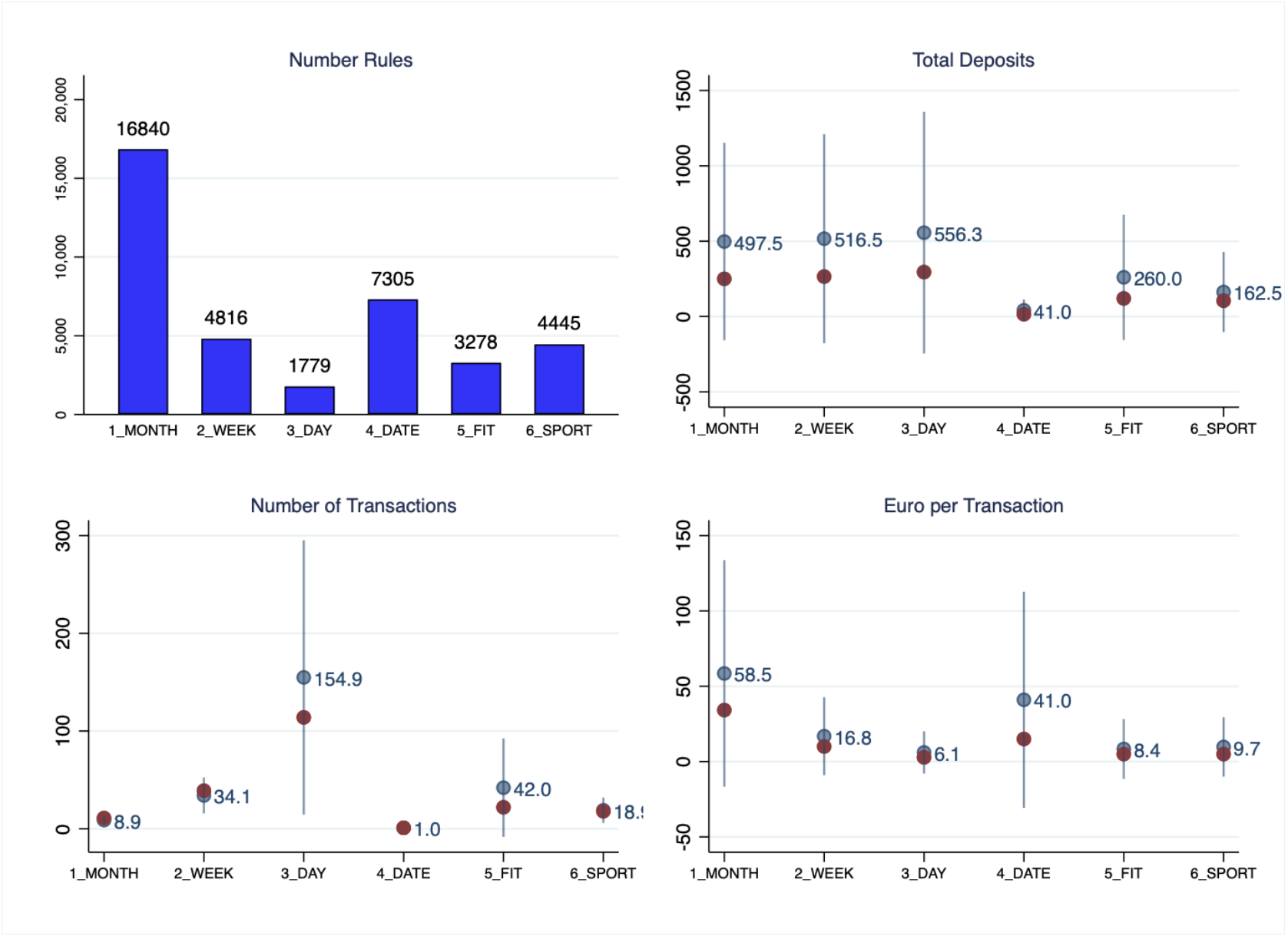


Figure 2: This figure displays the relation between the number of deposits and the amount deposited associated with recurring rules. To ensure statistics are based on the same standardized window of one year, the sample is restricted to all rules created between January 2021 and December 2023 (i.e., excluding the last year of the sample) and on transactions happening within 365 days from rule creation. The top-left panel displays the number of rules created. The top-right panel displays the distribution of total euros deposited. The bottom-left panel displays the distribution of the number of transactions. The bottom-right panel displays the distribution of the euro per transaction. Blue circles denote means, while red circles denote medians.

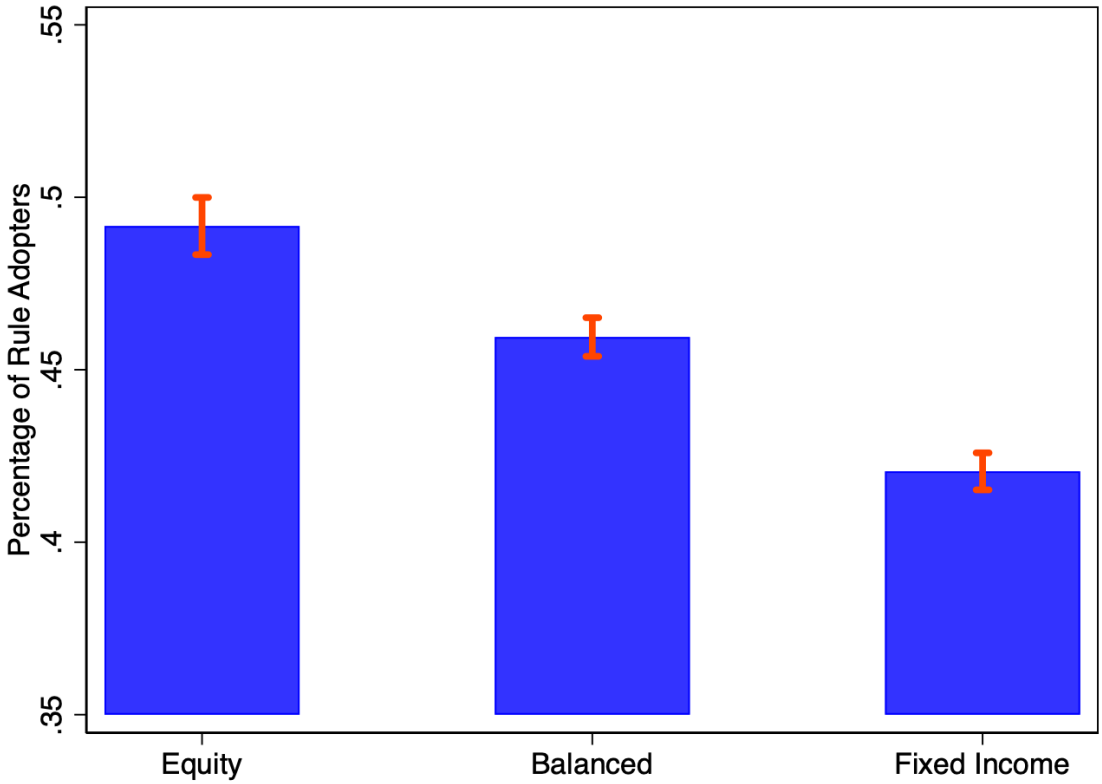


Figure 3: This figure reports the fraction of users who adopt a saving rule, conditional on the type of fund they invest in, i.e., equity, balanced, and fixed-income funds. The red bars represent 95% confidence intervals.

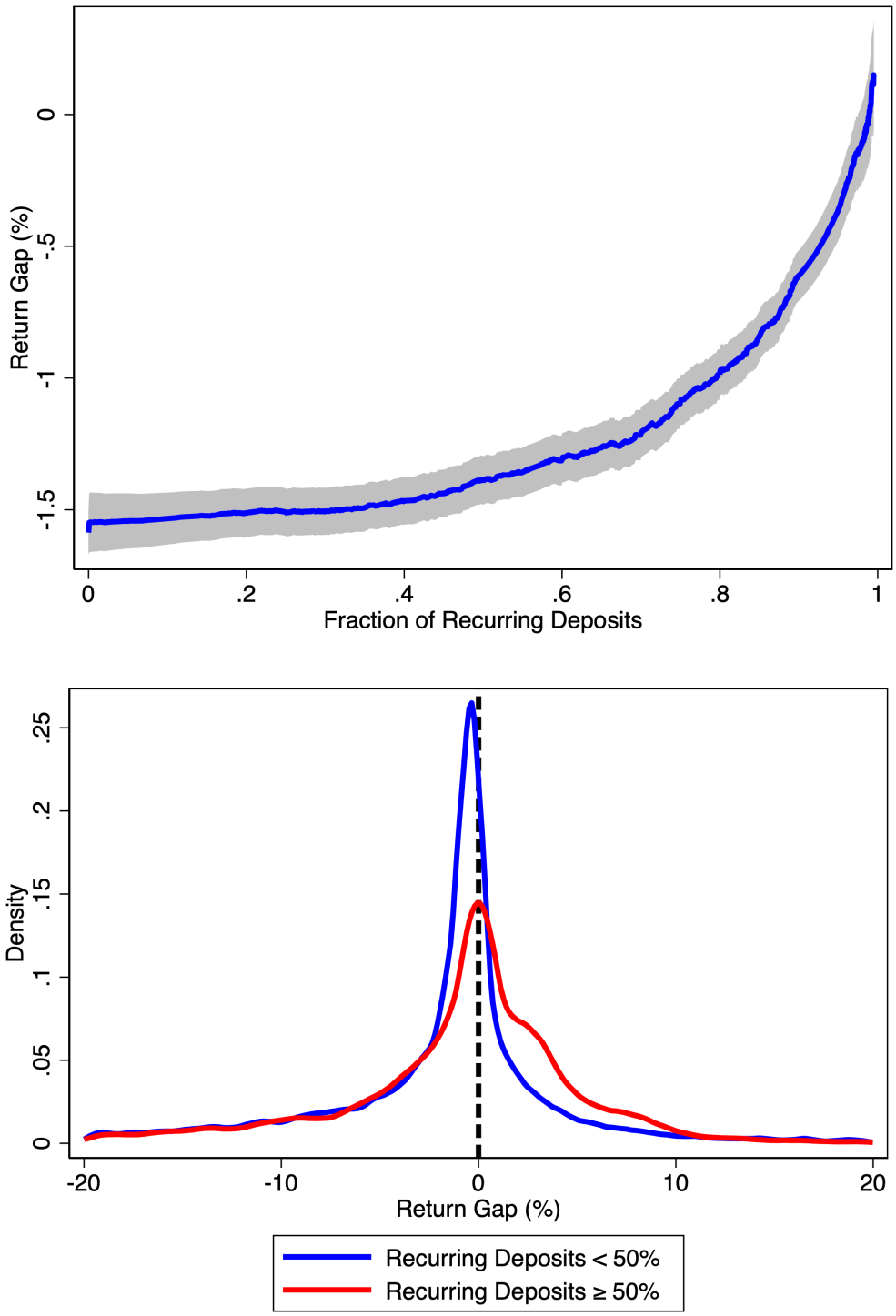


Figure 4: The top panel displays the relation between the *Return_Gap* and the fraction of recurring deposits using a symmetric nearest neighbor smoothing procedure. The bottom panel displays kernel densities of the *Return_Gap* for users who automate less (more) than 50% of their deposits, denoted by blue (red) lines. In both figures, the *Return_Gap* is measured at the user-fund level, and is the difference between the dollar-weighted return of the user in the fund and the return of the fund over the same period.

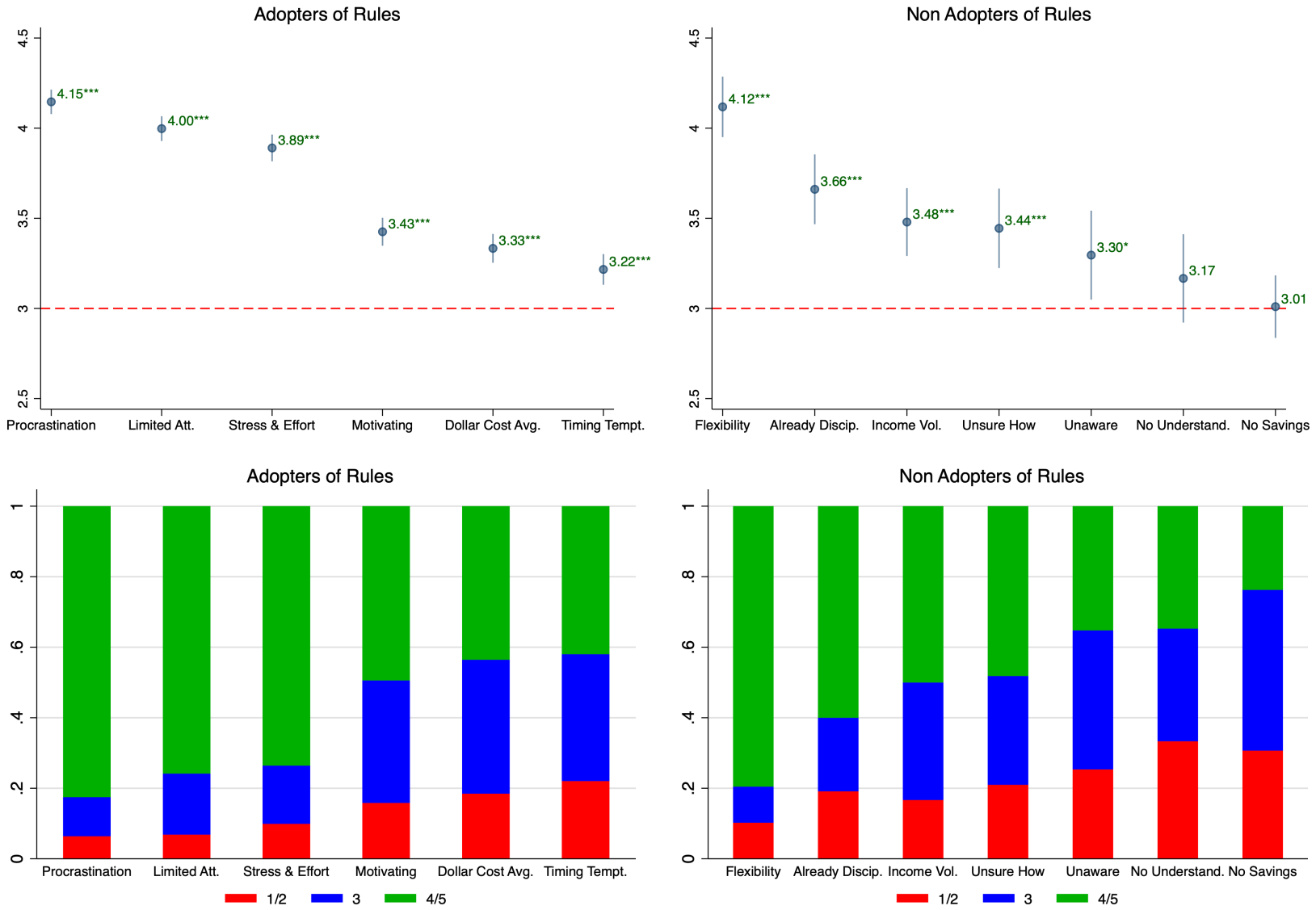
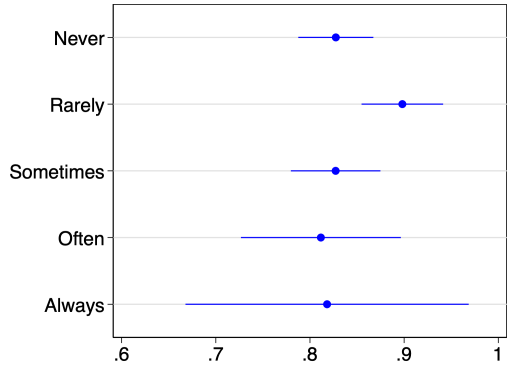
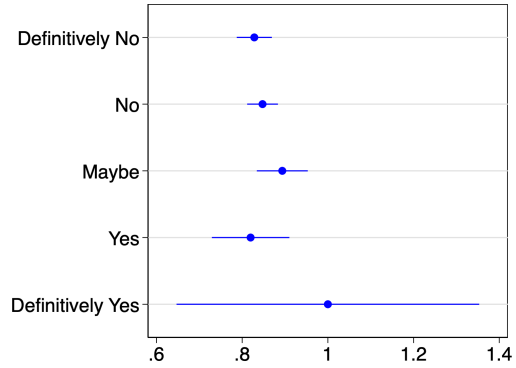


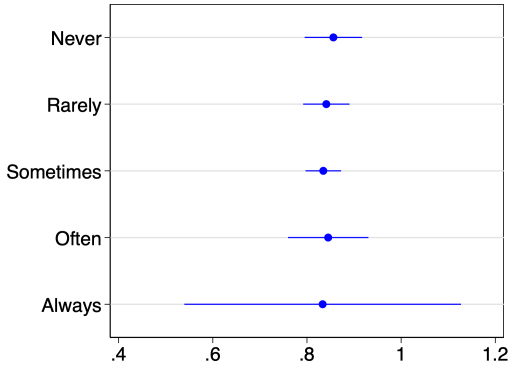
Figure 5: The upper panels display the average Likert-scale ratings, together with 95% confidence intervals, that respondents assign to various statements regarding recurring investment rules. Respondents evaluated each statement on a scale from 1 ("not important at all") to 5 ("very important"). Lower panels display the fraction of respondents assigning a score of i) either 1 or 2, ii) 3, and iii) either 4 or 5. The Left panels refer to adopters of rules who are asked to evaluate the following statements on rules: (i) *Help avoid procrastinating on saving* (labelled as "Procrastination" on the x-axis), (ii) *Save time by reducing the need to monitor the markets* ("Limited Attention"), (iii) *Eliminate the stress and mental burden of making decisions each time* ("Stress & Effort"), (iv) *Are fun and motivating* ("Motivating") (v) *Take advantage of volatility to lower the average purchase price (dollar-cost averaging)* ("Dollar Cost Avg."), and (vi) *Avoid the temptation to time the market* ("Timing Tempt."). The right panels refer to non-adopters of rules who are asked to evaluate the following statements: (i) *I want to decide how much to save based on circumstances* ("Flexibility"), (ii) *I'm already disciplined and invest regularly* ("Already Discip."), (iii) *My income is too variable* ("Income Vol."), (iv) *I don't know how to create the best rule for me* ("Unsure How"), (v) *I don't know what a savings rule is* ("Unaware"), (vi) *I don't understand how it works* "No Understand."), and (vii) *I don't have money to save* ("No Savings"). In the upper figures, averages marked with ***, **, and * are significantly different from 3 (i.e., a neutral stance) at the 1%, 5%, and 10% levels.



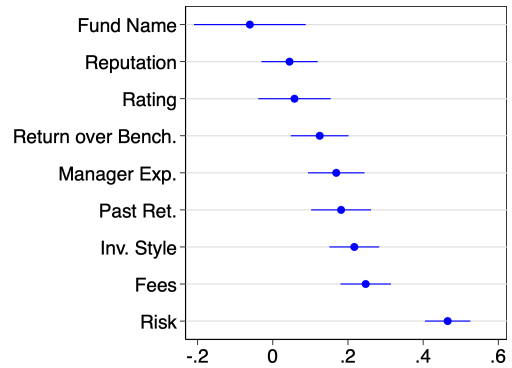
(a) To what extent do you time the market?



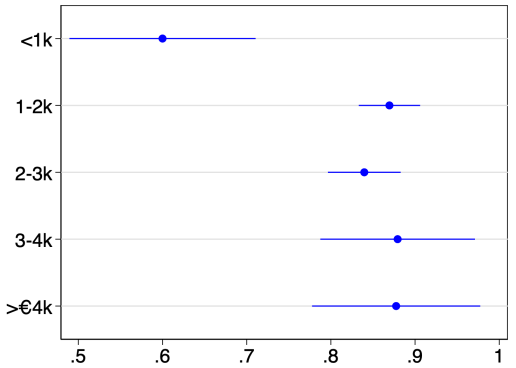
(b) Do you have the tools to time the market?



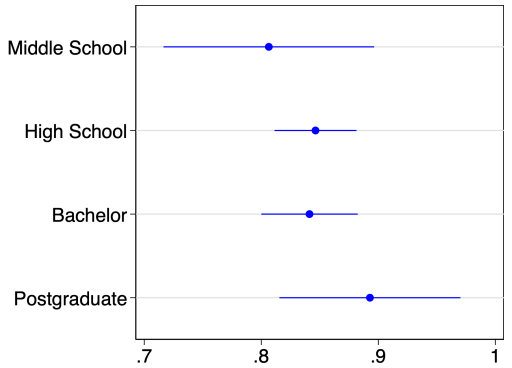
(c) Do funds' past returns predict future returns?



(d) Which factors do you consider most important when investing in a mutual fund?



(e) Income



(f) Education

Figure 6: This figure displays coefficient estimates and 95% confidence intervals for the following cross-sectional regressions: $\mathbb{1}_{Rule\_Adopter_i} = \sum_{k=1}^{K} \mathbb{1}_{\{X_{i,k}=1\}} + \epsilon_i$ where $\mathbb{1}_{Rule\_Adopter_i}$ is a dummy equal to one if respondent i has ever adopted a rule. The term $\mathbb{1}_{\{X_{i,k}=1\}}$ is an indicator variable equal to 1 if individual i belongs to group k, with K denoting the total number of mutually exclusive groups for a given characteristic. These regressions are separately estimated for the following dimensions (a) responses to the question *"To what extent do you follow a market timing strategy, that is, trying to identify the best moment to enter or exit the markets in order to maximize returns?"*, (b) responses to the question *"Do you think you have the tools to predict market trends?"*, (c) responses to the question *"Do you think that a fund's past returns predict its future returns?"* (d) responses to the question *"Which of these factors do you consider most important when investing in a mutual fund?"* (e) Income, and (f) Education. Each regression is estimated without a constant, so that the coefficient on each indicator represents the average adoption rate for respondents in the corresponding group.

Table 1. Summary Statistics

Panel A. Demographic Characteristics

	Obs	Mean	Std	p1	p25	p50	p75	p99
Age	51,776	36.05	11.97	20	27	33	42	73
Female	51,776	0.18	0.39	0	0	0	0	1

Panel B. Transactions

	Obs	Mean	Std	p1	p25	p50	p75	p99
Tenure	56,243	20.15	16.29	1.00	3.41	18.03	35.15	47.77
Num. Deposits (Monthly)	56,243	2.56	5.17	0.03	0.38	1.00	2.09	24.91
Net Deposits (Monthly)	56,243	92.31	272.40	0.15	5.00	23.26	78.19	1,151.87
Num. Funds	56,243	1.47	1.05	1	1	1	1	6
Equity (%)	56,240	11.84	28.89	0.00	0.00	0.00	0.00	100.00
Balanced (%)	56,240	42.54	46.60	0.00	0.00	2.08	100.00	100.00
Fixed Income (%)	56,240	45.60	47.04	0.00	0.00	25.00	100.00	100.00

Panel C. Funds

	Return	Std	Sharpe	p1	p25	p50	p75	p99
				C.1 Equity				
America	1.65	15.44	0.11	-9.72	-3.92	-0.08	3.68	10.39
Asia pacific	8.53	12.90	0.66	-8.13	-1.49	0.68	2.77	9.66
Europe	2.98	13.77	0.22	-10.71	-2.31	0.03	3.26	9.37
Global	5.13	9.34	0.55	-8.21	-1.70	0.15	2.78	8.17
Emerging Markets	3.79	14.39	0.26	-10.26	-2.47	-0.06	2.96	11.77
Italy	3.36	12.99	0.26	-10.65	-2.30	-0.08	2.31	10.85
				C.2 Balanced				
Patrimonio Esente	-0.39	5.42	-0.07	-7.78	-1.08	-0.07	1.16	5.17
Strategia Moderata	6.28	4.66	1.35	-1.88	-0.64	0.72	1.09	3.88
Patrimonio Dinamico	-0.66	5.96	-0.11	-5.73	-1.46	-0.18	0.95	6.46
Strategia Crescita	11.15	7.90	1.41	-3.06	-0.42	0.89	2.22	5.03
Strategia Dinamica Globale	2.49	7.59	0.33	-7.62	-1.56	-0.15	2.10	7.11
				C.3 Fixed-Income				
Risparmio	2.51	0.36	6.90	-0.04	0.14	0.23	0.29	0.44
Breve termine	-1.73	4.54	-0.38	-7.94	-1.24	-0.03	1.51	6.91
Performance	-2.58	7.16	-0.36	-8.47	-1.51	-0.10	1.65	7.18

Panels A and B report 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, standard deviation, as well as the $1st$, $25th$, $50th$, $75th$, and $99th$ percentiles. Panel A refers to the demographic characteristics: *Age*, the user's age as of 2024; *Gender*, the user gender (1 for males and 0 for females); Panel B refers to users' transactions: $Num.\ Funds$, the number of funds with at least one transaction; *Tenure*, the number of months from the first to the last transaction; $Num.\ Deposits(Monthly)$, the average number of deposits per month; $Deposits(Monthly)$, the average deposit amount; $Equity(\%)$, the fraction of deposits into Equity funds; $Balanced(\%)$, the fraction of deposits into Balanced funds, and $FixedIncome(\%)$, the fraction of deposits into Fixed Income funds. Panels C report cross-sectional averages for mutual funds available to the users on the App. Panels C.1, C.2, and C.3 refer to Equity, Flexible, and Fixed-Income funds, respectively. *Return*, is the Annualized Return, Vol, is the Annualized Volatility, *Sharpe*, is the Annualized Sharpe Ratio, while $1st$, $25th$, $50th$, $75th$, and $99th$ denote the percentiles of monthly returns.

Table 2. Adoption and Usage of Investment Rules

Panel A.1 Adoption (Pooled Across Rules)

	Obs	Mean	Std	p1	p25	p50	p75	p99
Use Rule	56,243	0.41	0.49	0.00	0.00	0.00	1.00	1.00
Num. Rules	22,788	2.55	3.76	1.00	1.00	1.00	3.00	8.00
Num. Rules (Type)	22,788	1.56	0.92	1.00	1.00	1.00	2.00	4.00

Panel A.2 Deposits (Pooled Across Rules)

	Obs	Mean	Std	p1	p25	p50	p75	p99
Euro Rules (%)	22,788	0.73	0.29	0.13	0.55	0.84	0.98	1.00
Euro Rules (€)	22,788	1,764.40	3,703.84	20.00	150.00	600.00	1,950.00	7,080.00
Euro Total (€)	22,788	2,577.81	5,151.99	40.00	260.00	965.00	2,800.78	10,170.72

Panel B.1 Adoption (by type)

	Obs	Mean	Std	p1	p25	p50	p75	p99
MONTH	22,788	0.86	0.35	0.00	1.00	1.00	1.00	1.00
WEEK	22,788	0.18	0.39	0.00	0.00	0.00	0.00	1.00
DAILY	22,788	0.08	0.27	0.00	0.00	0.00	0.00	1.00
DATE	22,788	0.14	0.35	0.00	0.00	0.00	0.00	1.00
FIT	22,788	0.15	0.35	0.00	0.00	0.00	0.00	1.00
SPORT	22,788	0.16	0.36	0.00	0.00	0.00	0.00	1.00

Panel B.2 Deposits (by type)

	Obs	Mean	Std	p1	p25	p50	p75	p99
MONTH EURO (%)	19,516	0.85	0.27	0.19	0.81	1.00	1.00	1.00
MONTH EURO	19,516	1,456.89	2,960.99	20.00	140.00	500.00	1,610.00	5,839.00
WEEK EURO (%)	4,131	0.62	0.35	0.04	0.29	0.66	1.00	1.00
WEEK EURO	4,131	1,379.05	2,748.21	18.00	130.00	475.00	1,410.00	5,705.00
DAILY EURO (%)	1,843	0.46	0.40	0.00	0.05	0.39	0.94	1.00
DAILY EURO	1,843	1,471.31	5,679.33	5.00	20.00	176.00	1,190.00	6,534.00
DATE EURO (%)	3,186	0.20	0.29	0.01	0.03	0.08	0.21	1.00
DATE EURO	3,186	206.80	534.67	5.00	25.00	80.00	200.00	800.00
FIT EURO (%)	3,339	0.32	0.31	0.01	0.06	0.20	0.49	1.00
FIT EURO	3,339	431.24	948.13	5.00	39.00	134.00	420.00	1,735.00
SPORT EURO (%)	3,544	0.30	0.31	0.02	0.08	0.19	0.42	1.00
SPORT EURO	3,544	357.60	780.00	10.00	53.00	155.00	370.00	1,300.00

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, standard deviation, as well as the $1st$, $25th$, $50th$, $75th$, and $99th$ percentiles. $Use\ Rule(Dummy)$ is a dummy equal to 1 if an individual has ever used a rule and 0 otherwise, $Number\ Rules$ is the number of rules ever created by a user, $Number\ Rules\ (Type)$ is the number of rule types (i.e., whether JOR, SPR, DSP, etc.) ever created by a user, $Euro\ Rules$ (%), is the share of total Euro deposited on the App using rules, $N.Trans\ Rules$ (%), is the share of the total number of deposits made on the App using rules, $Euro\ Rules$, is the total amount deposited on the App using rules, $N.Trans\ Rules$, is the total number of deposits on the App using rules, $Euro\ Total$, is the total amount deposited on the App, $N.Trans\ Total$, is the total number of deposits on the App.

Table 3. Rules and Type of Fund

Panel A: Rule Creation

	All	*Equity*	*Balanced*	*Fixed-Income*
$Ret_{[-1,-7]}$	-0.133	0.203	-1.004	-0.092
	(-0.82)	(1.28)	(-0.81)	(-0.12)
$Ret_{[-8,-30]}$	0.477***	0.520***	1.535	0.499
	(3.08)	(4.03)	(1.39)	(0.65)
$Ret_{[-31,-60]}$	0.308**	0.434***	0.191	1.221**
	(2.46)	(3.93)	(0.19)	(2.15)
$Ret_{[-61,-180]}$	0.310***	0.437***	0.680	1.305***
	(5.05)	(5.84)	(1.47)	(4.13)
$Ret_{[-18,-360]}$	0.052	0.127**	-0.303	0.092
	(0.93)	(2.16)	(-0.66)	(0.23)
Adj R^2	0.017	0.018	0.018	0.019
Obs	29,328,516	6,500,893	11,000,011	11,826,141

Panel B: Rule Deletion

	All	*Equity*	*Balanced*	*Fixed-Income*
$Ret_{[-1,-7]}$	-0.517***	-0.452***	0.524	-0.544
	(-2.69)	(-3.00)	(0.53)	(-0.81)
$Ret_{[-8,-30]}$	-0.293**	-0.502***	-0.174	-0.068
	(-2.35)	(-3.85)	(-0.22)	(-0.15)
$Ret_{[-31,-60]}$	-0.148*	-0.404***	0.066	-0.362
	(-1.77)	(-3.25)	(0.09)	(-0.94)
$Ret_{[-61,-180]}$	-0.123**	-0.243***	0.192	-0.265
	(-2.49)	(-4.28)	(0.43)	(-1.05)
$Ret_{[-18,-360]}$	-0.139***	-0.221***	0.120	0.102
	(-4.33)	(-3.65)	(0.51)	(0.53)
Adj R^2	0.024	0.019	0.025	0.031
Obs	29,328,516	6,500,893	11,000,011	11,826,141

Panels A and B report coefficient estimates and associated t-statistics (in parentheses) of the following regression model:

$$\begin{aligned}\mathbb{1}\{Rule\}_{i,j,t} = \alpha_i + \alpha_t + \beta_1 Ret_{j,[-1,-7]} + \beta_2 Ret_{j,[-8,-30]} \\ + \beta_2 Ret_{j,[-31,-60]} + \beta_3 Ret_{j,[-61,-180]} + \beta_4 Ret_{j,[-181,-360]} + \epsilon_{i,j,t}\end{aligned}$$

where $\mathbb{1}\{Rule\}_{i,j}$ is a dummy variable equal to 1 if user i has created (in Panel A) or deleted (in Panel B) a rule in fund j at time t; $Ret_{j,[-t_1,-t_2]}$ denote returns of fund j in between the t_1 and t_2 prior days; α_i and α_t denote user and time fixed-effect. The t-statistics are based on standard errors clustered at the user and time level. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

Table 4. Recurring Rules and Savings

Panel A: Deposits

	Total	*Manual*	*Recurring*
$\mathbb{1}\{Rule\}$	87.74***	-2.95**	90.69***
	(35.59)	(-2.23)	(43.37)
Mean $\mathbb{1}\{Rule\} = 0$	26.54	26.54	0
Time FE	YES	YES	YES
USER FE	YES	YES	YES
Adj R^2	0.48	0.32	0.66
Obs	1,331,618	1,331,618	1,331,618

Panel B: Withdrawals

	Total	*Manual*	*Recurring*
$\mathbb{1}\{Rule\}$	-14.68***	-14.68***	–
	(-8.94)	(-8.94)	(–)
Mean $\mathbb{1}\{Rule\} = 0$	8.71	8.71	–
Time FE	YES	YES	–
User FE	YES	YES	–
Adj R^2	0.15	0.15	–
Obs	1,331,618	1,331,618	–

Panel C: Net Saving

	Total	*Manual*	*Recurring*
$\mathbb{1}\{Rule\}$	102.42***	11.73***	90.69***
	(33.75)	(5.92)	(43.37)
Mean $\mathbb{1}\{Rule\} = 0$	17.83	17.83	0
Time FE	YES	YES	YES
USER FE	YES	YES	YES
Adj R^2	0.35	0.21	0.66
Obs	1,331,618	1,331,618	1,331,618

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

$$Y_{i,t} = +\beta \mathbb{1}\{Rule\}_{i,t} + a_i + \tau_t + \epsilon_{i,t}$$

where $Y_{i,t}$ denotes either Deposits (Panel A), Withdrawals (Panel B) or Net-saving (Panel C), of user i in month t, $\mathbb{1}\{Rule\}$ denotes a dummy variable equal to one if user i has an active rule in month t, a_i denotes a user fixed-effect, and τ_t a monthly fixed-effect. Column *Total* reports results based on all transactions (i.e., the sum of manual transactions and those based on a recurring rule), while columns *Manual* and *Recurring* report results for only manual and recurring transactions, respectively. Because Withdrawals can only be performed manually, we do not report any estimate under column *Recurring* in Panel B. Standard errors are double-clustered by time and user. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

Table 5. The Causal Effect of Recurring Rules on Saving

	Panel A: Deposits		
	OLS	IV	ITT
$\mathbb{1}\{Rule\}$	3.770***	9.865**	
	(6.65)	(2.55)	
$\mathbb{1}\{Encouraged\}$			1.468***
			(3.03)
α	1.199***	0.043	1.567***
	(6.52)	(0.06)	(7.52)
R-Square adj	0.114	–	0.019
N	517	517	517
	Panel B: Withdrawals		
	OLS	IV	ITT
$\mathbb{1}\{Rule\}$	0.176**	0.400	
	(2.57)	(1.20)	
$\mathbb{1}\{Encouraged\}$			0.060
			(1.21)
α	0.064***	0.021	0.083***
	(3.91)	(0.34)	(4.19)
R-Square adj	0.025	–	0.002
N	517	517	517
	Panel C: Net-Saving		
	OLS	IV	ITT
$\mathbb{1}\{Rule\}$	3.594***	9.465**	
	(6.48)	(2.51)	
$\mathbb{1}\{Encouraged\}$			1.409***
			(2.97)
α	1.135***	0.022	1.483***
	(6.35)	(0.03)	(7.35)
R-Square adj	0.109	–	0.018
N	517	517	517

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

$$Y_i = \alpha + \beta \mathbb{1}\{Rule\}_i + \epsilon_i \qquad Column(1)$$
$$Y_i = \alpha + \beta \widehat{\mathbb{1}\{Rule\}}_i + \epsilon_i \qquad Column(2)$$
$$Y_i = \alpha + \beta \mathbb{1}\{Encouraged\} + \epsilon_i \qquad Column(3)$$

where $Y_{i,t}$ denotes either the daily average deposit (Panel A), withdrawal (Panel B), or net-saving (Panel C) of user i, $\mathbb{1}\{Rule\}$ denotes a dummy variable equal to one if user i has created a rule, $\widehat{\mathbb{1}\{Rule\}}$ denotes a dummy variable equal to one if user i has created a rule instrumented by $\mathbb{1}\{Encouraged\}_i$, a dummy if the user was targeted by the marketing campaign. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

Table 6. Deposits and Past Returns

	Panel A: All Funds		Panel B: Equity		Panel C: Balanced		Panel D: Fixed-Income	
	Manual	*Recurring*	*Manual*	*Recurring*	*Manual*	*Recurring*	*Manual*	*Recurring*
$Ret_{[-1,-7]}$	0.07**	-0.11	0.04	-0.02	0.05**	-0.13	0.07	-0.15
	(2.14)	(-0.35)	(1.66)	(-0.09)	(2.10)	(-0.30)	(0.94)	(-0.26)
$Ret_{[-8,-30]}$	0.06**	-0.01	0.06**	0.00	0.05**	-0.01	0.01	0.04
	(2.41)	(-0.03)	(2.60)	(0.02)	(2.13)	(-0.03)	(0.09)	(0.12)
$Ret_{[-31,-60]}$	0.05**	-0.05	0.03*	0.01	0.01	-0.05	0.02	-0.06
	(2.27)	(-0.26)	(1.78)	(0.03)	(0.52)	(-0.12)	(0.26)	(-0.12)
$Ret_{[-61,-180]}$	0.05***	0.02	0.05***	0.05	0.02	0.03	-0.01	0.06
	(6.04)	(0.20)	(3.83)	(0.47)	(1.04)	(0.09)	(-0.29)	(0.22)
$Ret_{[-181,-360]}$	0.02***	-0.02	0.03**	0.01	0.00	-0.09	0.01	-0.07
	(2.84)	(-0.40)	(2.66)	(0.08)	(0.16)	(-0.65)	(0.15)	(-0.35)
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
User FE	YES	YES	YES	YES	YES	YES	YES	YES
Adj R^2	0.09	0.10	0.07	0.11	0.06	0.10	0.11	0.09
Obs	55756790	55756790	9526787	9526787	23196458	23196458	23033545	23033545

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

$$Deposit_{i,j,t} = \beta_1 Ret_{j,[-1,-7]} + \beta_2 Ret_{j,[-8,-30]} + \beta_2 Ret_{j,[-31,-60]} + \beta_3 Ret_{j,[-61,-180]} + \beta_4 Ret_{j,[-181,-360]} + \alpha_i + \alpha_t + \epsilon_{i,j,t}$$

where $Deposit_{i,j,t}$ denotes deposits of user i in fund j on day t, $Ret_{j,[-t_1,-t_2]}$ denote returns of fund j in between the t_1 and t_2 prior days; α_i and α_t denote user and time fixed-effect. Columns *Manual* and *Recurring* report results for manual and recurring transactions, respectively. Results in Panel A are based on all funds, while Results in Panels B, C, and D are based on Equity, Balanced, and Fixed-Income mutual funds, respectively. Standard errors are double-clustered by time and user. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

Table 7. Recurring Rules and Return Gap

Panel A: All Funds

	All	*Positive*	*Negative*
$\%Rule$	0.99***	0.58***	1.59***
	(16.08)	(8.58)	(13.27)
α	-1.62***	-1.37***	-1.94***
	(-47.02)	(-33.85)	(-33.02)
Adj R^2	0.006	0.003	0.010
Obs	44,744	26,481	18,263

Panel B: Fund Type

	Equity	*Balanced*	$Fixed-Income$
$\%Rule$	0.47***	0.63***	1.69***
	(3.29)	(7.14)	(16.23)
α	-1.44***	-1.72***	-1.61***
	(-17.36)	(-33.18)	(-29.07)
Adj R^2	0.001	0.003	0.016
Obs	8,991	18,831	16,903

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

$$Return\_Gap_{i,j} = \alpha + \beta \ \ \%Rule_{i,j} + \epsilon_{i,j}$$

where $Return\_Gap_{i,j}$ denotes the difference between the dollar-weighted return of user i in fund j and the return of fund j over the same period. $\%Rule_{i,j}$ denotes the fraction of deposits made with a Rule by user i in fund j. Results in Panel A are based on all funds, while in Panel B, they are based on Equity, Balanced, and Fixed Income. Standard errors are robust to heteroscedasticity. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

Table 8. Pairwise Tests of Mean Equality

Panel A: Adopters of Rules

	Procrastination	Lim. Attention	Stress	Motivating	Dollar Cost Avg.	Timing Tempt.	N_Beat	N_Beaten
Procrastination		3.65***	5.36***	14.03***	15.15***	16.24***	5	0
Lim.Attention	-3.65***		1.75*	10.95***	12.30***	13.48***	4	1
Stress	-5.36***	-1.75*		9.20***	10.58***	11.82***	3	2
Motivating	-14.03***	-10.95***	-9.20***		1.82*	3.31***	2	3
Dollar Cost Avg.	-15.15***	-12.30***	-10.58***	-1.82*		1.55	0	4
Timing Tempt.	-16.24***	-13.48***	-11.82***	-3.31***	-1.55		0	4

Panel B: Non Adopters

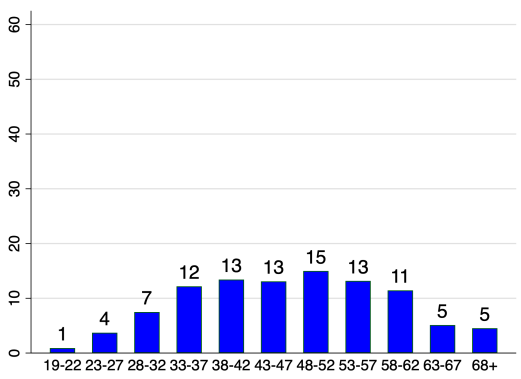
	Flexibility	Already Discip.	Volatile Income	UnsureHow	Unaware	No Understand	No Savings	N_Beat	N_Beaten
Flexibility		3.50***	5.01***	4.71***	5.12***	5.79***	7.79***	6	0
Already Discip.	-3.50***		1.43	1.49	2.32**	3.06***	4.62***	3	1
Volatile Income	-5.01***	-1.43		0.25	1.37	2.13**	3.61***	2	1
Unsure How	-4.71***	-1.49	-0.25		1.00	1.73*	2.99***	2	1
Unaware	-5.12***	-2.32**	-1.37	-1.00		0.75	1.64	0	2
No Understand	-5.79***	-3.06***	-2.13**	-1.73*	-0.75		0.76	0	4
No Savings	-7.79***	-4.62***	-3.61***	-2.99***	-1.64	-0.76		0	4

This Table displays the results from non-parametric two-sample mean equality tests. We display the z-score from the Wilcoxon rank-sum test and the associated level of significance (***, **, and * denote 1%, 5%, and 10% significance levels, respectively). Panel A refers to the Likert questions for the adopters of recurring investment rules, while Panel B refers to the Likert questions for the non-adopters. We test the null that the mean of the responses to the motive in each row is equal to the mean of the responses to the motives in each column. In Panel A, the labels "Procrastination," "Lim. Attention," "Stress and Effort," "Motivating," "Dollar-cost Averaging," and "Timing Temptation" refer to the following motives: (i) *Help avoid procrastinating on saving*, (ii) *Save time by reducing the need to monitor the markets*, (iii) *Eliminate the stress and mental burden of making decisions each time*, (iv) *Are fun and motivating*, (v) *Take advantage of volatility to lower the average purchase price (dollar-cost averaging)*, (vi) *Avoid the temptation to time the market.* In Panel B, the labels "Flexibility," "Already Discilined," "Volatile Income," "Not Know How," "Unaware," "No understanding," and "Not enough savings" refer to the following motives: (i) *I want to decide how much to save based on circumstances*, (ii) *I'm already disciplined and invest regularly*, (iii) *My income is too variable*, (iv) *I don't know how to create the best rule for me*, (v) *I don't know what a savings rule is*, (vi) *I don't understand how it works*, and (vii) *I don't have money to save.* For the motive in each row, the column labeled as N.Beat displays the number of tests resulting in a positive rejection of the null (i.e., mean being significantly larger), while the column labeled as N.Beatean displays the number of tests resulting in a negative rejection of the null (i.e., mean being significantly smaller).

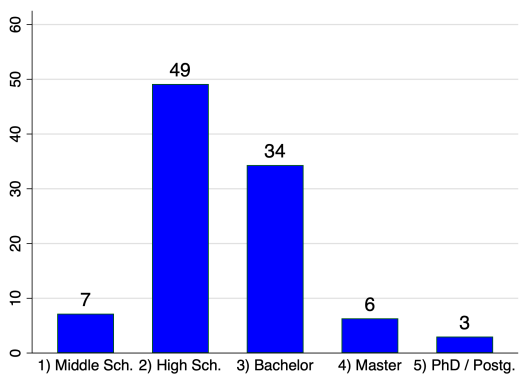
Online Appendix for:

Set it and Forget it:
Engineering Investment Habits with FinTech

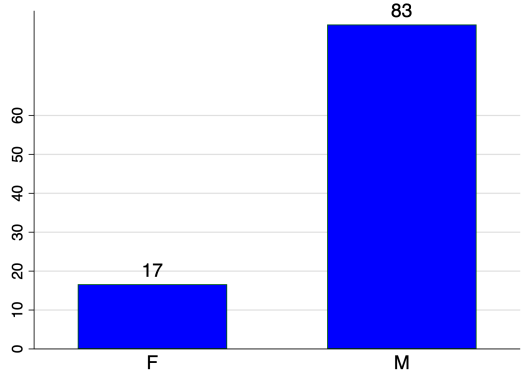
A Additional Figures and Tables



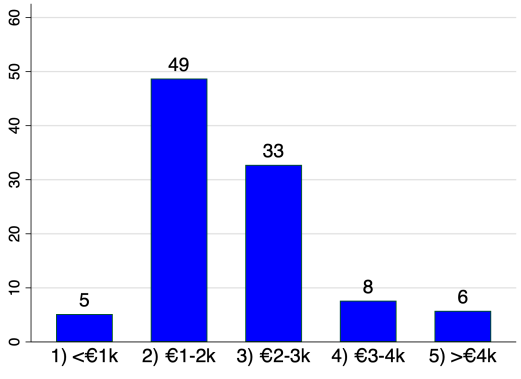
(a) Age



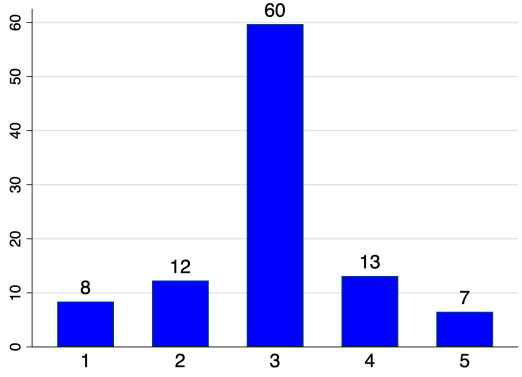
(b) Education



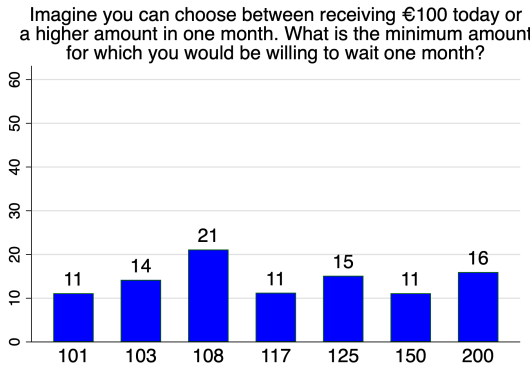
(c) Gender



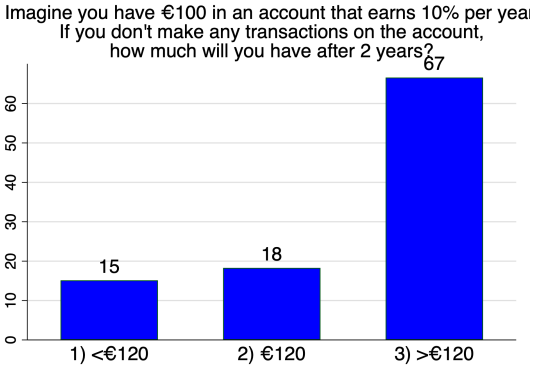
(d) Income



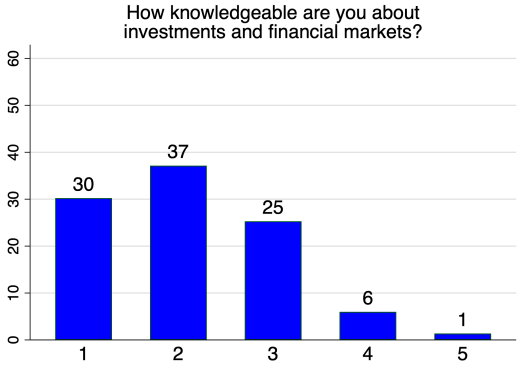
(e) Risk Propensity



(f) Impatience



(g) Fin Literacy



(h) Fin Literacy (Self)

Figure A.1: This figure displays the distribution of the demographic characteristics described in Section 2.2.

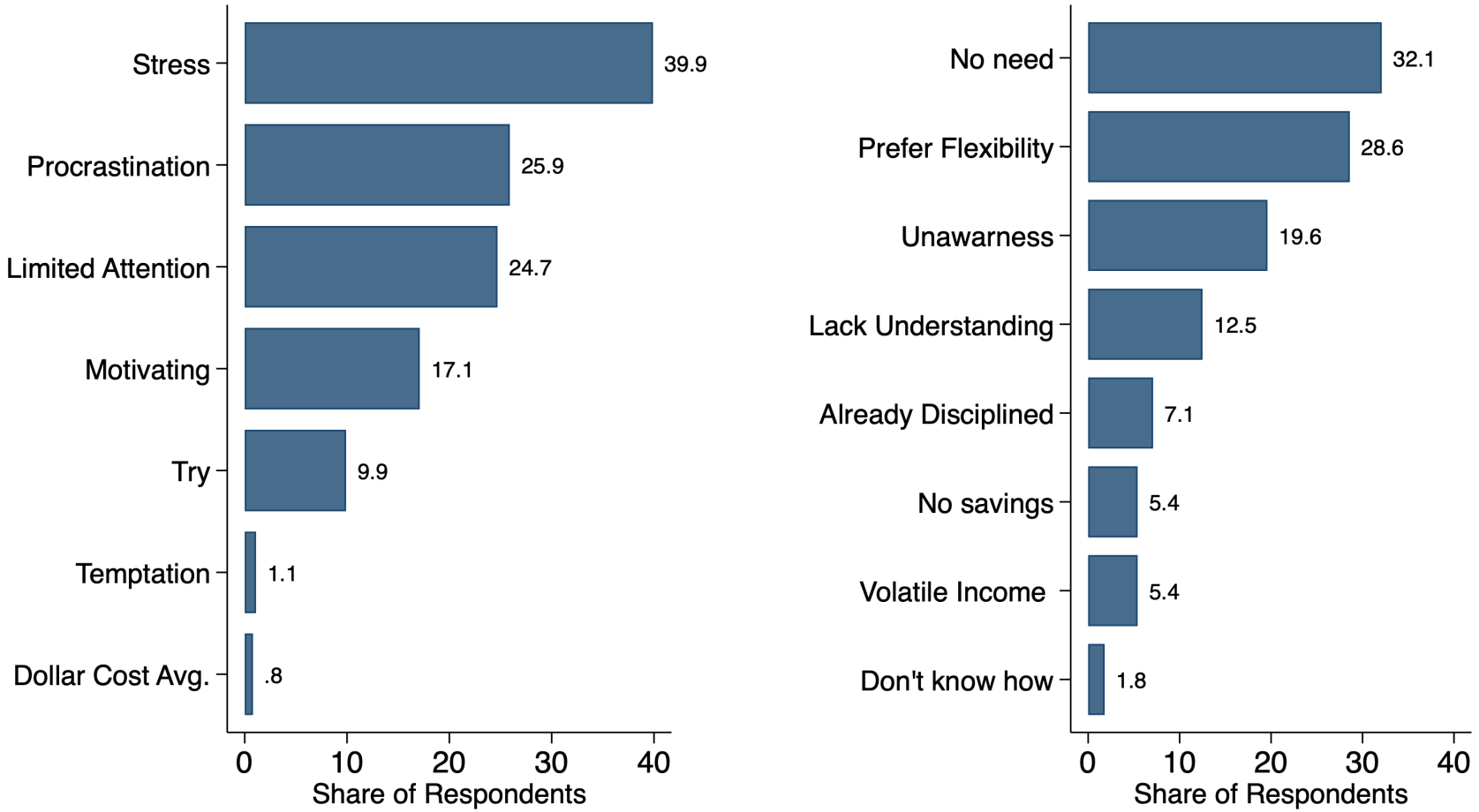


Figure A.2: The Figure displays the share of respondents mentioning any of the topics displayed on the y-axis in the open questions. The left panel refers to rule adopters who were asked "*Why did you decide to create a recurring savings rule?*", while the right panel refers to non-adopters who were asked: "*Why have you not created a recurring savings rule?*". See Section 6.2 for the list of keywords used to identify the topics.

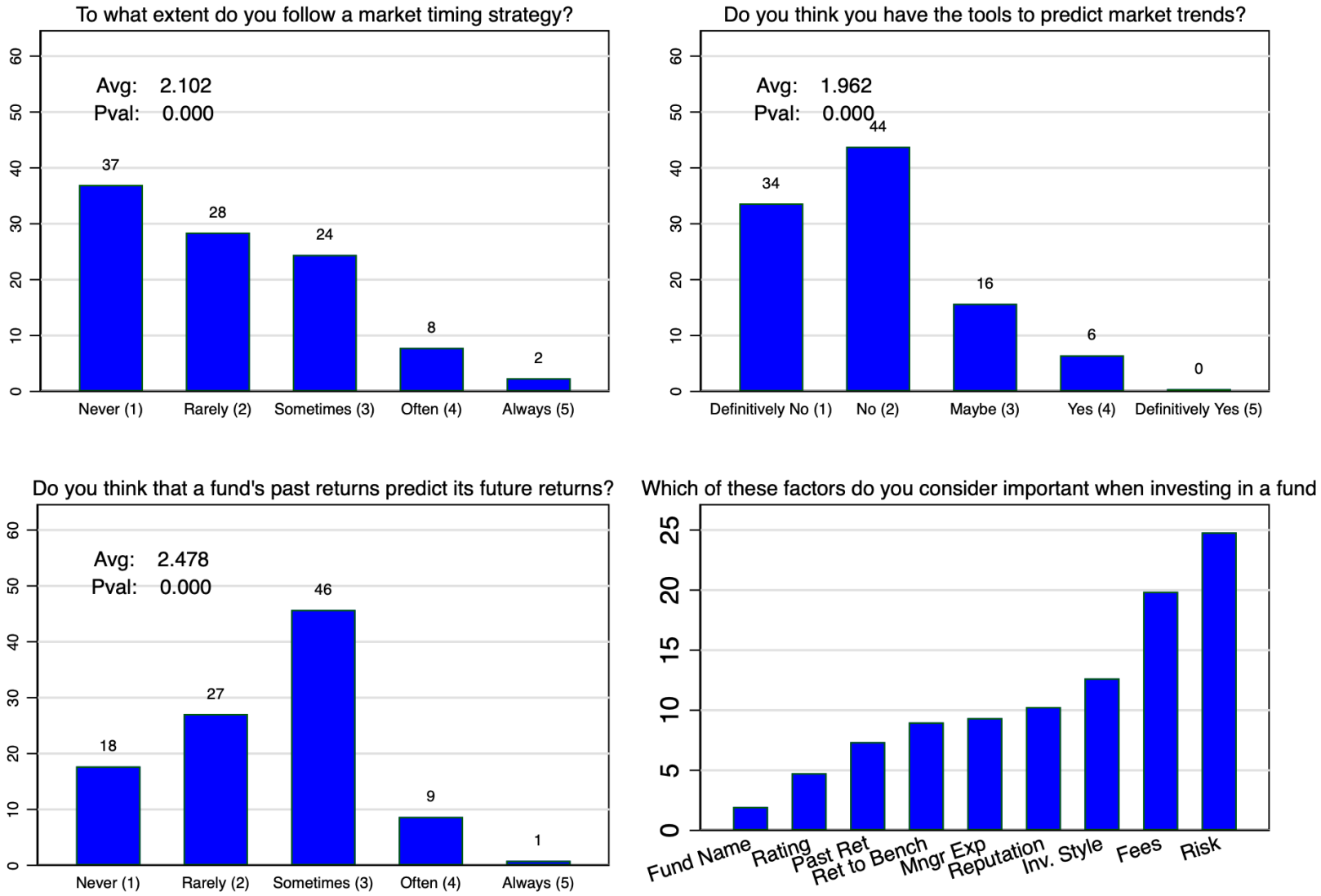


Figure A.3: The top-left panel displays the distribution of the responses to the question "*To what extent do you follow a market timing strategy, that is, trying to identify the best moment to enter or exit the markets in order to maximize returns?*" The top-right panel displays the distribution of the responses to the question "*Do you think you have the tools to predict market trends?*" The bottom-left panel displays the distribution of the responses to the question"*Do you think that a fund's past returns predict its future returns?*" The bottom-right panel displays the distribution of the responses to the question "*Which of these factors do you consider most important when investing in a mutual fund?*".

Table A.1. Recurring Rules and Saving

Panel A: Deposits

	> 2 Months	> 4 Months	> 6 Months
$\mathbb{1}\{Rule\}$	91.03***	94.68***	96.11***
	(35.60)	(29.19)	(25.44)
Mean $\mathbb{1}\{Rule\} = 0$	49.62	60.29	65.34
Time FE	YES	YES	YES
USER FE	YES	YES	YES
Adj R^2	0.44	0.42	0.42
Obs	745,151	534,248	428,825

Panel B: Withdrawals

	> 2 Months	> 4 Months	> 6 Months
$\mathbb{1}\{Rule\}$	-9.62***	-6.85***	-5.78***
	(-5.92)	(-4.26)	(-3.58)
Mean $\mathbb{1}\{Rule\} = 0$	14.71	16.35	16.83
Time FE	YES	YES	YES
User FE	YES	YES	YES
Adj R^2	0.14	0.14	0.15
Obs	745,151	534,248	428,825

Panel C: Net Saving

	> 2 Months	> 4 Months	> 6 Months
$\mathbb{1}\{Rule\}$	100.65***	101.53***	101.89***
	(33.07)	(28.99)	(26.38)
Mean $\mathbb{1}\{Rule\} = 0$	34.91	43.94	48.51
Time FE	YES	YES	YES
USER FE	YES	YES	YES
Adj R^2	0.32	0.31	0.31
Obs	745,151	534,248	428,825

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

$$Y_{i,t} = +\beta \mathbb{1}\{Rule\}_{i,t} + a_i + \tau_t + \epsilon_{i,t}$$

where $Y_{i,t}$ denotes either Deposits (Panel A), Withdrawals (Panel B), or Net-saving (Panel C), of user i in month t, $\mathbb{1}\{Rule\}$ denotes a dummy variable equal to one if user i has an active rule in month t, a_i denotes a user fixed-effect, and τ_t a monthly fixed-effect. Results are based on all transactions (i.e., the sum of manual transactions and those based on a recurring rule). Columns (1), (2), and (3) report results for users with at least 2, 4, and 6 manual deposits, respectively. Standard errors are double-clustered by time and user. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

B Survey Questions

Sezione 1 di 3: Uso Delle Regole di Risparmio

[Q1] Hai mai **utilizzato** una **regola di risparmio**?

- ○ Si
- ○ No
- ○ Non so / Non ricordo

IF Response to Q1 is "No"

Perchè non hai mai usato una **regola di risparmio**?

_____

_____

Quanto sono stati **importanti** i seguenti **motivi per la tua decisione** di non usare una regola?

	Per niente	Poco	Neutrale	Abbastanza	Molto
Non so come creare la regola migliore per me	○	○	○	○	○
Sono già disciplinato e investo regolarmente	○	○	○	○	○
Voglio **decidere** quanto risparmiare **in base delle circostanze**	○	○	○	○	○
Le mie **entrate sono troppo variabili**	○	○	○	○	○
Non ho soldi da risparmiare	○	○	○	○	○
Non capisco il funzionamento	○	○	○	○	○
Non so cosa sia una regola di risparmio	○	○	○	○	○

IF Response to Q1 is "Yes"

Perchè hai aperto una **regola di risparmio**?

_____

_____

Quanto sono stati **importanti** i seguenti **motivi per la tua decisione** di usare una regola?

	Per Niente	Poco	Neutro	Abbastanza	Molto
Aiuta a **non procrastinare** il risparmio	○	○	○	○	○
Riduce la tentazione di anticipare il mercato	○	○	○	○	○
Elimina lo **stress e il costo mentale di decidere** ogni volta	○	○	○	○	○
Fa risparmiare tempo, riducendo la necessità di seguire i mercati	○	○	○	○	○
È **divertente e motivazionale**	○	○	○	○	○
Sfrutta la volatilità per abbassare il prezzo medio d'acquisto (**dollar-cost averaging**)	○	○	○	○	○

Hai mai **chiuso una regola**?

○ Si

○ No

○ Non ricordo

Perchè hai deciso di chiudere una regola? (seleziona una o più opzioni)

- [ ] Il **fondo** non ha avuto i **rendimenti** che mi aspettavo
- [ ] È diventata **insostenibile**
- [ ] La mia **situazione finanziaria** è cambiata
- [ ] È diventata **noiosa o poco motivante**
- [ ] Ne ho aperta **un'altra**
- [ ] **Ho risparmiato** quanto mi ero prefissato
- [ ] Altro (specifica sotto)

Sezione 2 di 3: La tua opinione sui mercati finanziari

In che misura segui una strategia di **market timing,** ovvero cerchi di individuare il **momento migliore per entrare o uscire** dai mercati per massimizzare i rendimenti?

- ○ Mai
- ○ Raramente
- ○ Qualche volta
- ○ Spesso
- ○ Sempre

Pensi di avere **gli strumenti per prevedere** l'andamento dei mercati?

- ○ Assolutamente No
- ○ No
- ○ Non So
- ○ Si
- ○ Assolutamente Si

Pensi che i **rendimenti passati** di un fondo **predicano i rendimenti futuri**?

- ○ Mai
- ○ Raramente
- ○ Qualche volta
- ○ Spesso
- ○ Sempre
- ○ Non so

Quali **fattori** ritieni più **importanti** per la **scelta di un fondo** di investimento? (seleziona una o più opzioni)

- [ ] Profilo di **rischio**
- [ ] I **rendimenti passati**
- [ ] **Rendimento** rispetto al **benchmark**
- [ ] **Stile** di investimento
- [ ] **Costi e commissioni**
- [ ] **Valutazioni** di agenzie **esterne** (es. Morningstar)
- [ ] **Esperienza** del **gestore**
- [ ] **Fama** e reputazione della **società di gestione**
- [ ] **Nome** del fondo

Sezione 3 di 3: La tua opinione sui mercati finanziari

Immagina di avere **€100** su un conto che rende il **10% all'anno**. Se **non fai nessuna operazione** sul conto, quanto avrai **dopo 2 anni**?

- ○ Meno di €120
- ○ €120
- ○ Più di €120

Quanto sei **esperto di investimenti** e mercati finanziari?

- ○ Non esperto
- ○ Poco esperto
- ○ Mediamente esperto
- ○ Abbastanza esperto
- ○ Molto esperto

Immagina di poter scegliere tra avere **€100 oggi** o una somma **più alta tra un mese**. Qual è la somma **minima** per cui sei disposto ad **aspettare** un mese?

- ○ €101
- ○ €103
- ○ €108
- ○ €117
- ○ €125
- ○ €150
- ○ €200

In una scala da 1 a 5, Quanto sei disposto a prendere **rischi nei tuoi investimenti**?

- ○ 1, Evito rischi a tutti i costi
- ○ 2
- ○ 3, Provo a bilanciare rischi e rendimenti dei miei investimenti
- ○ 4
- ○ 5, Voglio rendimenti più alti possibili anche se questo implica prendere tanto rischio

In media, pensi che **rispetto agli altri investitori** di Gimme5 i **tuoi rendimenti** siano?

- ○ Molto peggiori
- ○ Peggiori
- ○ Simili
- ○ Migliori
- ○ Molto migliori

Qual è il tuo livello di **istruzione**?

- ○ Scuola Media
- ○ Scuola Superiore
- ○ Laurea triennale
- ○ Laurea Magistrale
- ○ Master
- ○ Dottorato

Qual è il tuo **reddito netto mensile**?

- ○ Meno di €1.000
- ○ Tra €1.001 e €2.000
- ○ Tra €2.001 e €3.000
- ○ Tra €3.001 e €4.000
- ○ Più di €4.000
- ○ Preferisco non rispondere