The Promises and Pitfalls of Robo-advising

Francesco D'Acunto,* Nagpurnanand Prabhala,† Alberto G. Rossi‡

Abstract

Individual investors are underdiversified. They often bear excessive idiosyncratic risk, and barely benefit from market risk premia. We study a FinTech intervention, a robo-advising portfolio optimizer that constructs tailored diversification strategies based on investors' holdings and preferences. We study the extent of technology adoption, its determinants, and out- comes such as investment returns and the nature and extent of trading after adoption, using a large sample of individual brokerage accounts with data on investor characteristics, holdings, trades, and investor-brokerage interactions. Preliminary results show that adopters are similar to non-adopters in terms of demographics, but have more assets under management and trade more with the brokerage house. Adopters also appear to be more sophisticated as their trades have superior risk-adjusted performance compared to non-adopters. The robo-advising tool has opposite effects depending on investors' level of diversification before adoption. It increases portfolio diversification dramatically for those that held less than 5 stocks before adoption. For these investors, the optimizer also increases the market-adjusted returns of trades, but not fees. At the same time, robo-advising reduces stock-holdings for those investors that held more than 50 stocks before adoption. It also increases the fees they pay, but not the market-adjusted returns of their trades. For both groups, robo-advising increases attention to portfolio performance through higher online account logins, and exacerbates behavioral biases, such as the tendency of stock sales to outperform stock purchases.

JEL classification: D14, G11, O33

Keywords: FinTech, Portfolio Choice, Individual Investors, Financial Literacy, Behavioral Biases, Technology Adoption.

*R.H.Smith School of Business, University of Maryland, College Park, MD, USA. e-Mail: fdacunto@rhsmith.umd.edu

†R.H.Smith School of Business, University of Maryland, College Park, MD, USA. e-Mail: nprabhala@rhsmith.umd.edu

‡R.H.Smith School of Business, University of Maryland, College Park, MD, USA. e-Mail: arossi@rhsmith.umd.edu.

1 Introduction

Household finance studies how individuals make financial investments, such as risky investments in the stock market. As Campbell (2006) and Campbell and Viceira (2002) point out, most investors would benefit from stock market participation because of the high risk premia in stock markets. The benefits of participation, however, depend on the structure of the portfolios investors hold. In the data, risky holdings deviate considerably from the predictions of theory (Badarinza, Campbell, and Ramadorai, 2016). In particular, individual investors tend to be undiversified. Financial advising can potentially help mitigate under-diversification, nudge investors towards more diversified portfolios, and thus help investors realize better outcomes. At the same time, financial advisors might themselves display behavioral biases or cognitive limitations, and hence be unable to provide effective advising (Linnainmaa, Melzer, and Previtero, 2016).

In this paper, we ask whether FinTech robo-advising tools allow investors to increase their diversification and to reduce well-known behavioral biases, and, if yes, at what cost these results can be achieved. We study the introduction of a robo-advising tool – an automated portfolio optimizer – by a full service brokerage house in India. Our unique data include information on investors' demographic characteristics, as well as their trading histories, portfolio holdings, performance, and interactions with human advisors before and after adopting the tool.

We use these data to address three sets of questions. First, we study the determinants and modes of adoption of the robo-advising portfolio optimizer. We assess whether users and non-users differ based on observable characteristics, which informs on which categories of investors are more receptive to technological innovation in the realm of financial advice. Our preliminary results show that users and non-users are indistinguishable along several demographic characteristics, including their gender, age, and experience – measured as the number of years they have held an account with the brokerage house. Users and non-users differ in that users have a larger amount of wealth invested with the brokerage house. Users also appear to be more directly involved with the management of their portfolios as they login more frequently to their online accounts, and make call to their advisers more often than the non-users. Finally, users also appear to be more sophisticated as their trades have superior risk-adjusted performance compared to non-users. We also assess whether investor characteristics can explain investors' differential reaction to the robo-advice. That is, whether they use the tool but do not trade based on its advice, whether they follow the advice only partially, or whether they follow the advice completely.

Second, we study the effects of adopting the optimizer's advice on the diversification and risk-return properties of investors' portfolios. In Section 3, we describe the mechanics of the robo-advising tool. The tool uses Markowitz mean-variance optimization to provide optimal portfolio weights. It uses 3 years of data to estimate the variance-covariance matrix of the stocks held, and uses modern techniques such as shrinkage of the variance-covariance matrix as well as short-selling constraints to guarantee well-behaved portfolio weights. A peculiar feature of the tool is that the suggested portfolio is based not only on the set of stocks the investor holds at the time of use of the tool, but also on up to 15 additional stocks, which the brokerage house chooses among the most liquid stocks in the Indian stock market each day. The robo-advising tool produces automatically the set of trades the investor would need to place to rebalance his/her portfolio based on the recommendations, and the investor can place these trades in batch mode by merely clicking a button.

We interpret the robo-advisor as a way to simplify the set of decisions investors have to make to rebalance their portfolio allocations. When investors have no access to the tool, rebalancing requires a complex set of decisions. Investors face the daunting task of picking a few securities among hundreds that are available for trade. After picking stocks, they need to decide how to allocate their wealth among the chosen stocks. To simplify this set of problems, investors often focus their decision-making process on individual trades by rolling mental accounts once they close a position and open a new one (see Frydman, Hartzmark, and Solomon, Forthcoming), as opposed to focusing on the characteristics of their full portfolio at each point in time. The robo-advising tool therefore reduces the multi-dimensional portfolio problem faced by investors into a simple decision.

We analyze the effects of robo-advising on portfolio diversification, risk, and investment returns. As far as diversification is concerned, we would expect – if the tool is successful – an increase in the diversification of those investors that were the least diversified before using the tool, but little to no impact on those investors that were already highly diversified. Consistently, our preliminary results show that the effect of using the portfolio optimizer on the number of stocks investors hold is strongly monotonic based on the number of stocks investors held before usage. Following the optimizer's advice increases dramatically the number of stocks held by the least diversified investors – those holding less than 5 stocks before usage – whereas the effect goes to zero for investors that held between 6 and 30 stocks. The effect becomes negative for investors that held more than 30 stocks. For the latter group, the decrease in the number of stocks held suggests that the short-selling constraints bind, and the optimizer recommends these investors to close their positions in stocks that should have been shorted had the constraint not been in place. Our preliminary results focus on the change in the number of stocks held before and after usage. In Section 5.1 of this proposal, we describe the other diversification outcomes we will consider, which include measures of portfolio concentration and measures of portfolio volatility.

These preliminary results suggest that the bulk of the benefits of robo-advising is concentrated among the investors that would need diversification the most. Moreover, they suggest that assessing the effects of robo-advising requires we account for the dramatically different levels of diversification across investors before usage. We therefore move on to assess the effects of the usage of the portfolio optimizer on trading performance and trading behavior across investors, based on their levels of diversification before usage. In our preliminary results, all investors increase the number of trades they place after using the portfolio optimizer. But the market-adjusted trading performance of the ex-ante under-diversified investors improves after using the optimizer, while the performance of the ex-ante diversified investors does not change. At the same time, ex-ante diversified investors pay higher brokerage fees for the higher number of trades after usage, whereas ex-ante under-diversified investors do not pay higher fees. In Section 5.1, we describe the other measures of performance we will consider, such as investors' aggregate portfolio returns.

Third, we focus on a set of biases the finance literature has attributed to individual investors. Usage of the portfolio optimizer appears to increase the trading activity of all investors, and hence one might worry that it could enhance the biases that have been documented in the literature. This could be a downside of using the robo-advising tool which, contrary to a human advisors, has no way to debias investors or to emphasize the negative consequences of certain trading behaviors.[1]

In our preliminary results, we build on Odean (1999), who find that the returns of the stocks sold by individual investors tend to be higher than the returns of the stocks they purchase. We show that this tendency is also prevalent among the investors in our sample before the adoption of the robo-advising tool. Consistent with our conjecture, this tendency becomes more prevalent within investors after the

[1] Note that recent research suggests human advisors might themselves be subject to behavioral biases, and hence transmit such biases to the trading behavior of their clients (see Linnainmaa, Melzer, and Previtero, 2016).

use of the portfolio optimizer compared to before. Also, consistent with the conditional results on trading activity and performance described above, we find that the increase in this tendency is more pronounced for investors that were more diversified before usage, as opposed to investors that were under-diversified before usage. In Section 5.1, we describe the other behavioral biases we will consider, which include the disposition effect and the home-bias effect.[2]

The results described above are based on single-differences tests, in which we compare diversification, trading behavior, and trading performance within individuals, before and after usage of the portfolio optimizer. The single-differences tests allow us to ensure our results are not driven by systematic, time-invariant differences across investors that use or do not use the portfolio optimizer, and hence by the selection into usage of the portfolio optimizer.

In Section 5.2, we describe the research design and strategies we will employ to address a set of issues that single-differences tests cannot address. Results could be driven by unobserved time-varying characteristics of investors, which cause both the usage of the optimizer and the change in trading behavior before and after usage. For instance, an investor could decide he/she wants to trade more, and might think using the portfolio optimizer will give him/her ideas on which trades to place and how much to invest. The fact that our baseline single-differences results are very different based on the ex-ante diversification of investors alleviates this concern. In order to explain our results, time-varying shocks to trading motives should hit all investors at the same time, but should be very different across investors based on their level of diversification.

To address these identification problems more systematically, we propose a set of tests that we will implement as described in Section 5.2. The first test consists of restricting the analysis to investors that adopt the technology in July 2015. This is the month in which the portfolio optimizer was introduced for the first time by the brokerage house. The brokerage house had no underlying motivations for introducing it in July 2015 as opposed to any earlier or later month, apart from the fact that their technology team thought the device was ready to use broadly. This test will reduce concerns that time-varying shocks at the investor level determine both their adoption of the robo-advising technology, as well as the change in their trading behavior and performance.

We also propose falsification tests for the single-differences baseline design. The falsification tests will include assigning placebo dates of usage of the optimizer to investors that use it, so as to address

[2] Our data also include the municipalities and states in which investors reside, which we are in the process of coding.

the concern that a time-varying shock affected all users at the same time and determined their usage of the tool as well as their change in trading behavior. A second set of tests will exploit the full cross-section of investors we observe, that is, users and non-users of the portfolio optimizer. We will use the large pool of non-users to implement a nearest-neighbor matching procedure. We will match each user with a non-user that is similar based on a propensity score computed from demographic characteristics (age, gender, experience, location of residence) and users' trading behavior and performance before usage. Then, we will assess the change in trading behavior and performance – if any – of non-users, over the same time horizon in which we do observe changes in the trading behavior and performance of users. This set of tests aims to address the concern that time-varying shocks affecting similar categories of investors might explain their decisions to use the optimizer.

Finally, we propose tests to address the identification issues described above using a difference-in-differences strategy. We will exploit a unique feature of our data, that is, the fact that we observe in detail the interactions between each investor and the human advisors employed by the brokerage firm, in addition to their usage of the portfolio optimizer. We will therefore compare the behavior of investors that access both human advisors and the robo-advising tool before and after usage, to the behavior of investors that only access human advisors, before and after the introduction of the robo-advising tool. This set of tests will allow us to assess and explore the changes in investor behavior due to robo-advising versus advising in general (see Logg, 2017).

2 Related Literature

Our work contributes to multiple strands of literature in Finance and Economics. First, we contribute to the research in household finance. Campbell (2006) points out in his presidential address that the benefits of financial markets depend on how effectively households use financial products.[3]

Participation in the stock market is optimal from a portfolio allocation viewpoint given the historically high risk premia of stock market investments. However, attaining these high returns depends on the form of participation, specifically whether investors hold appropriately diversified portfolios. A robust empirical finding in the literature is that the actual risky holdings of investors deviate con-

[3]Recent work in this area addresses practical questions on the design or delivery of financial services and also informs policies such as those on tax, investor protection, financial literacy, or investor education. See, e.g., Anagol, Balasubramaniam, and Ramadorai (2017), Barber and Odean (2000, 2008), Barberis and Thaler (2003), Calvet, Campbell, and Sodini (2009), Grinblatt and Keloharju (2001a,b) for evidence on investor behavior.

siderably from theoretical predictions (Badarinza, Campbell, and Ramadorai, 2016). Participants in the stock market tend to be under-diversified. The under-diversification finding is robust across countries, and represents an empirical puzzle because it results in significant utility losses to investors. As Badarinza, Campbell, and Ramadorai (2016) point out, undiversified portfolios result in investors bearing idiosyncratic risk and this risk is not compensated by higher returns. Moreover, investors do not appear to correct this suboptimal investment behavior over time with experience.

Financial advising can potentially help mitigate underdiversification and help investors realize better outcomes (Gennaioli, Shleifer, and Vishny, 2015). But financial advisors are costly to access for individual investors, and might themselves be prone to behavioral biases or display cognitive limitations, and hence not advise their clients optimally (e.g., see Linnainmaa, Melzer, and Previtero, 2016). Our paper studies the effects of a "FinTech" robo-advising tool that makes it feasible for investors to access financial advice at low cost, and is not subject to advisor-specific behavioral biases. Yet, the robo-advising tool might replicate the mistakes and biases of those that coded it, and is prone to the same conflicts of interest of those that designed it, being them individuals or institutions. We describe the characteristics of the robo-advising tool we study in the next section.

A second contribution of our paper is the introduction of unique data on investor holdings and trades. A particular feature of interest is that we can tie investors' demographics, stock holdings, and trades to the usage of the robo-advising tool as well as to their interactions with human financial advisors. Because we track individual investment outcomes both before and after the adoption of the robo-advising tool, we can run a within-investor analysis of the effects of robo-advising on portfolio diversification, volatility, investor trading behavior as well as investors' overall performance. We can measure the extent of well-known behavioral biases in the ex-ante period, and test whether robo-advising alleviates or exacerbates them.

We also contribute to the broader Economics literature on technology adoption. The importance of technological progress dates back to at least Solow (1956). New technology and its adoption play an important role in improving productivity, as pointed out by a large literature on economic growth (Romer, 1990; Aghion and Howitt, 1992). The literature characterizes the generation of new technologies, the pace of adoption and related frictions (Griliches, 1957; Chari and Hopenhayn, 1991; Jovanovic and Nyarko, 1996; Jovanovic and Lach, 1997).

Comin and Mestieri (2014) review the literature on technology adoption. They point out that the key difficulty is the non-availability of micro-level datasets to study the patterns of technology adoption. Gaps are especially prominent in the intensive margin, that is, on the extent of usage of technology once adopted. Understanding the intensive margin is important because the production of innovation is concentrated, so technological progress is a matter of diffusion or adoption rather than just the creation of new technologies. We contribute to this literature by describing and analyzing granular, micro-level data on the likelihood and extent of adoption of technology in the investment realm, and on the effects of technology adoption on investment behavior and outcomes.

Our data allow us to measure both the intended and unintended effects of technology adoption, and to assess its overall effects. The recent literature on technology diffusion includes work on agriculture (Conley and Udry, 2010; Bold et al., Forthcoming), health products (Dupas, 2014), or manufacturing (Atkin et al., 2015). Manuelli and Seshadri (2014) analyze technological adoptions in the tractor industry between 1910 and 1960, while Skinner and Staiger (2015) and Chandra et al. (2016) study the role of innovation on the health care industry using Medicare data.

Our study sheds light on the potential and drawbacks of financial technology, or "FinTech." With few exceptions (e.g., Tufano, 1989), this is an area that has seen relatively little research. The relative scarcity of work on technological innovations in finance lead Frame and White (2004) to write that "... Everybody talks about financial innovation, but (almost) nobody empirically tests hypotheses about it" in reference to a quote attributed to Mark Twain.[4] Since the remark by Frame and White (2004), there has been work on introducing and evaluating new financial products aimed at the bottom of the financial pyramid, i.e. the poor, which are typically unbanked individuals unfamiliar with relatively well known financial products (e.g., see Dupas and Robinson, 2013). There is relatively little work on financial technology aimed at the investment decisions of high-income households. We contribute towards filling this gap.

3 Description of the Robo-advising Tool

The robo-advising technology we study – named *Portfolio Optimizer* – allows clients to use modern portfolio theory to compute the optimal weights in their investment account. Investors can access the portfolio optimizer from their online accounts. While investors have the option to enter the tickers they

[4]Everybody talks about the weather, but nobody does anything about it.

wish to consider in their portfolio allocation, the portfolio optimizer by default loads the investors' stock portfolio directly from their account. This feature of the optimizer aims at simplifying investors' access to the tool. This feature is very relevant for the scope of our research, because there is no possibility for the investor to make mistakes when reporting his/her portfolio holdings at the time of the portfolio optimization.

By default, the optimizer maximizes the investor's Sharpe ratio. The investor also has the option to specify the expected risk or return of the portfolio, but this occurs in less than 5% of the cases. When used, the application proposes the optimal portfolio weights according to Markowitz mean-variance optimization. To estimate the variance-covariance matrix, the algorithm uses three years of historical daily observations. To limit the effects of estimation error and to guarantee well-behaved portfolio weights, the algorithm implements modern techniques, such as shrinkage of the variance-covariance matrix. Moreover, the tool imposes short-sale constraints. An additional constraint is that there is no request to the investor to contribute additional financial resources to their brokerage account to transition to the recommended portfolio. All these details of the computation of the optimal portfolio weights are accessible to investors. The application produces automatically the buy and sell trades the investor needs to place if he/she wants to follow the advice, and the investor can place these trades automatically in batch mode by simply clicking the option on the screen. This feature also contributes to making the optimizer highly accessible even to less financially and tech-savvy investors.

The portfolio optimizer also performs an "educational" purpose, because it depicts the efficient frontier for the investor, and shows him/her the position of the optimized portfolio on the frontier, as well as the position of the portfolio the investor holds at the time the optimizer is used. A peculiar feature of this portfolio optimizer is that the suggested portfolio is not only based on the set of stocks held by the investor at the time the tool is used, but also on up to 15 additional stocks, which the brokerage house chooses among the most liquid stocks in the Indian stock market each day. Therefore, by construction, the optimizer might increase the diversification of the investors' portfolios not only by modifying the existing weights of the portfolios, but also by increasing the number of stocks investors hold.

4 Data

We use four main datasets. Table 1 reports baseline demographic information (age, gender, and account age) for our full sample, as well as for the subsamples we use in the analysis – as described below.

The *Portfolio Optimizer dataset* collects all the individual instances in which a client of the brokerage house used the portfolio optimizer, from the date in which the optimizer was first introduced as an option to clients, that is, July 14, 2015, until February 17, 2017. For each instance, we observe the unique client identifier, the date and time of usage, and the ticker identifier and weight for each of the stocks in the optimizing portfolio. Figure 1 plots the overall number of portfolio optimizer requests each week (dashed line, left y-axis), as well as the first-time requests by each investor (dashed line, right y-axis). Requests peaked in July 2015, when the tool was introduced for the first time and heavily marketed to clients, and in July 2016, once the brokerage house ran a second round of advertising and marketing of the tool to their clients. The average weekly number of requests was around 2,000 over the period, of which about 1,200 were first-time requests.

The second dataset we use – *Transactions dataset* – collects the full trading history of each client of the brokerage house from April 1, 2015 until January 27, 2017. In this dataset, we observe the unique client identifier, the date and time of any transaction made by the client, the ticker of the company on which the client traded, the type of trade, the rupee amount and quantity of the stock traded, the market price of the stock at the time of the trade, whether the trade was executed through the advisor or autonomously by the investor, and the fees charged to the investor. Matching the *Transaction dataset* to the *Portfolio Optimizer dataset* allows us to study the trading behavior of each investor before and after the adoption of the portfolio optimizer.

The third dataset we use – *Holdings dataset* – collects the monthly asset holdings for each client. For the holdings, we observe the unique client identifier, the exact date and time at which the holdings snapshot was registered, the ticker of each security held, the quantity of the security held, and the overall number of assets in the portfolio. The *Holdings dataset* is only available from January 1, 2016 to January 1, 2017.

The last dataset we use – *Logins dataset* – includes all the instances in which an investor or the investor's human advisor connected to the investor's online account. For each login, we observe the date and time in which the account was accessed, whether the investor himself or his/her advisor accessed the account, and whether the access was successful or not. The login information is available for the period between April 1, 2015 and January 27, 2017.

5 Methodology and Research Design

In this section, we describe in detail the outcome variables we consider in the analysis, as well as the empirical designs we propose to address the three sets of questions described in the introduction.

5.1 Outcome Variables

We focus on three sets of outcome variables that we split in two groups: (i) trading behavior, and (ii) trading performance.

For ***trading behavior***, we consider measures of portfolio diversification, of trading activity, and of presence of behavioral biases.

For portfolio diversification, *Number of Stocks* is the number of individual stocks each investor holds over a specified period of time. Our baseline analysis compares each outcome variable in the three months before and after the date of usage of the robo-advising tool, and the date of usage is the actual date of usage or the placebo date of usage, as described in the research design below. *Portfolio Concentration* is the share of the overall portfolio constituted by the 4 largest holdings in rupee amount. *Portfolio HHI* is an Herfindahl index for the concentration of investors' portfolios.

Moving on to trading activity, *Number of Trades* is the number of individual trades each investor places in a specified period of time. We perform robustness analyses to show that the results are similar if we use narrower windows (e.g., 1 month before and after usage) or broader windows (e.g., 6 months before and after usage). *Trading Volume* is the overall value of the trades the investor places (in rupees) in a specified period of time. *Number of Logins* is the number of times the investor logs into his/her online brokerage account in a specified period of time, which we interpret as a measure of attention.

We also consider a set of variables that capture the extent to which investors are affected by well-known behavioral biases, both before and after using the robo-advising tool. *Disposition Effect* is defined based on Odean (1998) as the difference between the proportion of gains realized minus the proportion of losses realized over a specified period of time. The proportion of gains realized is the ratio between the gains realized each day and the total gains that could have been realized on that day. The proportion of losses realized is the ratio between the losses realized each day and the total losses that could have been realized on that day. *Home Bias* is defined as the number of stocks held by the investor of firms located in the same Indian state as the investor, over the total number of stocks of that state listed in the Indian stock market. *Buys Underperforming Sales* is defined – following Odean (1999) – as the difference between the ex-post returns of the stocks investors buy and the stocks investors sell.

For ***trading performance***, we compute measures of returns and market-adjusted returns both at the individual trade level and at the portfolio level. We also work with volatility. *Simple Return* is the return of each trade in the 1, 3, or 6 months after the trade is placed. *Market-adjusted Return* is the return of each trade in the 1, 3, or 6 months after the trade is placed, adjusted for the return of the Indian stock market (Nifty Index) over the same period. *Portfolio market-adjusted Return* is similarly defined but computed at the portfolio level. Finally, *Portfolio Volatility* is the realized volatility of the investor's portfolio.

5.2 Research Design

In our first exercise, we study the selection of individual investors into adopting the robo-advising technology. To do this, we start from the raw data. We use the sample of investors that place at least one trade during our sample period, and compare the demographic characteristics of investors that adopt and do not adopt the robo-advising tool. Moreover, we describe the cross-sectional variation of the trading performance and holdings of investors that do and do not adopt the tool.

Second, we investigate the extent to which the investors that use the robo-advising tool follow the advice they obtain from the machine. This analysis will be restricted to the subsample of investors that use the robo-advising tool at least once. We merge the sample of investors that place at least one trade with the sample of investors that use the portfolio optimizer tool at least once. Within this sample, we describe and compare three subgroups of investors, that is, the investors that follow the robo-advice fully after receiving it, the investors that do not follow the advice at all, and the investors that follow the advice only partially.

Third, we study the effects of using the robo-advising tool on investors' trading behavior and trading performance - the outcome variables for these tests are described above. We propose a set of research designs to address the issue that the choice to use the robo-advising tool might be endogenous, as it might be itself determined by investors' own past trading behavior and/or performance.

The first design is a **single-difference approach**, in which we only consider investors that use the portfolio optimizer, and compare their trading behavior and performance before and after the first usage of the optimizer. This single-difference approach allows us to ensure that no time-invariant characteristics of investors, or time-invariant systematic differences across investors, can drive any variation in trading behavior and performance we might observe in the data. A concern with the single-difference approach is that it does not allow us to rule out the possibility that investors decided to use the robo-advising technology at a time in which they wanted to change their overall trading behavior and performance more broadly. Note, however, that in order to explain our results, these potential time-variant individual-investor-level shocks should have opposite direction for investors that were underdiversified before usage and for those that were diversified before usage.

As a first pass to assess whether our results could be driven by time-varying unobservable shocks that explain both technology adoption and change in trading behavior and performance, we will limit the analysis to portfolio optimizer users that used the machine during the first month the brokerage house introduced the new tool, that is, in July 2015. The timing of the introduction of the robo-advising tool was decided by the brokerage house, and not by the individual investors, and this timing alleviates the concern that usage is correlated with a broader decision to change trading behavior, at least for the investors that use the optimizer shortly after the brokerage house makes it available. The brokerage house did not introduce the tool based on business cycle considerations, but it did introduce it once their technology team thought the tool was ready to be accessed by the clients.

To further address the selection concerns in the usage of the robo-advising tool, we propose a set of **falsification tests**. In the first falsification test, we will only consider the investors that use the portfolio optimizer. We will assign to each investor a placebo date for the first usage of the tool, that is, a fictitious date of usage, so that the actual date of usage does not fall within three months before or after the placebo date. We then compare the trading behavior and performance of the investors over the three months before and after the placebo date of usage. This falsification test allows us to assess whether the actual date of usage of the portfolio optimizer coincides with other unobserved and concurrent shocks, which in turn affect investors' trading behavior and performance.

In the second falsification test, we will employ a matching strategy. We will exploit the large group of investors that never used the portfolio optimizer, and match each user with his/her nearest neighbor based on a propensity score. The propensity score is computed using the investors' demographic characteristics, as well as their trading behavior and performance before the date of usage of the portfolio optimizer. For each matched non-user, we assign a placebo date of usage, which is the date in which the matched treated investor indeed used the optimizer. We then compare the trading behavior and performance of the matched non-user in the three months before and after the placebo date. Under the assumption that matched investors are similar not only based on the observables we use to compute the propensity score, but also based on unobservables, this falsification test allows us to assess the extent to which unobserved time-variant investor characteristics might explain any change in trading behavior and performance after the date of usage of the portfolio optimizer.

Finally, we propose a test that allows us to assess whether our results are driven by the introduction of a robo-advising tool, or by investors' access to advice in general. If any change in behavior is driven by investors' access to advice in general, our results would suggest that robo-advising may be promising because it delivers financial advice at lower costs, compared to human advisors. If instead the change in behavior we observe is not due to exposure to any type of financial advice, but to robo-advising in particular, then our results would suggest that robo-advising tools are relevant beyond and above the mere decrease in the costs of accessing financial advice. To assess these two possibilities, we will exploit a unique feature of our data, that is, the fact that a set of investors is mapped permanently to human advisors throughout the sample period. These mapped investors have direct access to human advisors, and do reach out to them often. We propose a **difference-in-differences strategy** in which we only focus on the set of investors that are mapped to a human financial advisor throughout the sample period. Within this group, we will compare the performance and trading behavior of the investors that also use the robo-advising tool to the performance and trading behavior of the investors that do not use the tool, before and after the date in which the "treated" group uses the robo-advising tool. In this analysis, we interpret any change in trading behavior and performance of the treated group after the usage of the robo-advising tool as the incremental effect of robo-advising above and beyond the baseline effect of financial advice.

6 Preliminary Results

We conclude our proposal by describing some pieces of evidence based on the data we currently observe, and the research objectives described above. This set of preliminary results exemplify the methodologies we plan to use to address our questions fully in the next weeks.

6.1 Selection into the Adoption of Robo-advising

We compare a set of characteristics and outcome variables across users and non-users of the robo-advising tool to assess the extent to which they differ. We first compare characteristics across the two groups, irrespective of the timing, and hence pooling together the periods before and after the use of the portfolio optimizer. The cross-sectional differences described below therefore cannot be interpreted as the effects of using the portfolio optimizer on investors' trading behavior or invested wealth. Rather they capture the difference in characteristics between those that do and do not use the optimizer. In the next section, we describe the preliminary results for the single-differences analysis, which is restricted to users of the portfolio optimizer, and compares outcome variables before and after usage.

We start by comparing the time-invariant characteristics of investors that adopt the robo-advising tool to those that do not adopt the tool, whose trading activity we observe over the same period. Panel A of Table 2 compares these two subsamples. Adopters are slightly older than non-adopters, but we cannot reject the null that there is no difference. The average age of adopters is 46.2 years (median: 44.9 years), whereas the average age of non-adopters is 47.8 years (median: 46.9 years). The two groups are similar with respect to the other time-invariant characteristics we observe. The average fraction of men is 71% in both samples, and the average age of the account is 5.8 years in both sample. Overall, we fail to detect any economically or statistically significant difference in time-invariant demographics between users and non-users.

Table 2 also reports the main outcome variables across adopters and non-adopters of the robo-advising tool. Panel B focuses on investors' attention and trading behavior. Portfolio optimizer users are more attentive to their accounts. They login to their online accounts on average 658 times throughout our sample period, whereas non-user slog in on average 433 times. Users also place more trades on average (186 vs. 122), have a higher volume of trades (10.6 million rupees vs. 6.0 million rupees), and hence produce a larger amount of trading fees (17.7 thousand rupees vs. 10.07 thousand rupees). Overall, users of the robo-advising tool appear to be more active investors.

In Panel C of Table 2, we compare the trading performance of users and non-users, whereas in Panel D we compare the characteristics of their portfolios at a specified date – January 1st 2016. Two patterns emerge. First, users have a substantially higher amount of assets under management (AUM) and hold more stocks than non-users – differences are still detected but less substantial when comparing AUM and number of assets for non-stock securities, such as bonds, mutual funds, and ETFs. These other securities represent mere fractions of the value of the stock portfolios investors hold in our sample. Second, Panel C suggests that the performance of users dominates the performance of non-users over our sample period, although both underperform with respect to the market. The 1-month market-adjusted returns of stocks purchased are on average -0.86% for users and -1.22% for non-users. The 3-month market-adjusted returns are on average -2.55% for users and -3.60% for non-users.

The better trading performance of users despite their higher trading activity suggests that users might be more experienced and savvy than non-users. To assess this conjecture in the raw data, we compare the ex-post performance of the stocks purchased to the ex-post performance of the stocks sold. This comparison is based on Odean (1999), who document that the stocks individual investors sell tend to outperform the stocks they buy. As a rough measure of performance, we compare the market-adjusted returns at 1 and 3 months for the stocks each group of investors purchases and sells. As conjectured, users of the robo-advising tool seem less prone to sell future outperformers than non-users. The difference between the returns of stocks sold minus bought at the 1-month horizon is 0.44 percentage points for users, and 0.55 percentage points for non-users. The difference at the 3-month horizon is 0.76 percentage points for users, and 1.06 percentage points for non-users.

Overall, users of the robo-advising tool do not seem to differ substantially from non-users in terms of demographic and time-invariant characteristics, but they appear to be more sophisticated and to have a higher amount of AUM as well as higher trading activity than non-users.

6.2 Robo-advising and Portfolio Diversification

The first set of outcomes we consider are diversification outcomes. The robo-advising tool we analyze might allow investors to diversify their portfolios. This effect of the robo-advising tool would be relevant if it was stronger for investors that were more underdiversified before adopting the tool, and hence had a higher need for diversification, while possibly not being aware of it.

Table 2 highlights the large variation in the average number of stocks held by investors. Some investors are underdiversified – e.g., they only hold 1 or 2 stocks – whereas other investors hold a large number of stocks before using the optimizer. For investors that are diversified and hold a large number of stocks to begin with, the optimizer should not necessarily recommend an increase in the number of stocks. If anything, the optimizer might set some optimal weights to zero, because of the short-sale constraints.

To assess the effect of the portfolio optimizer on diversification, we compute the difference between the number of stocks each investor holds in the month after the first usage of the portfolio optimizer and the average number of stocks they held in the month before the first usage of the portfolio optimizer. We then compute the average difference separately for 5 groups of investors, based on the number of stocks they held before usage. Figure 2 reports the results of this exercise. In the top left panel, the bars represent the average difference between the number of stocks held after and before the first usage of the optimizer, which is measured on the y-axis. On the x-axis, we sort investors in 5 groups based on the number of stocks they held before using the optimizer. We report 90% confidence intervals around the estimated means.

The association between pre-usage number of stocks and change in the number of stocks held after usage displays an evident monotonic pattern. Investors that held 1 or 2 stocks before using the optimizer, and hence had the largest need to diversify their portfolio, increase the number of stocks they hold substantially after the first usage of the optimizer. The effect is positive both economically and statistically also for those holding between 3 and 5 stocks. The effect is instead not different from zero statistically or economically for those holding between 6 and 30 stocks. Moreover, the change becomes negative for those holding between 31 and 50 stocks, which is consistent with the notion that the optimizer might suggest to disinvest from stocks that should be shorted had the short-selling constraint not been in place.

Overall, this univariate analysis suggests that the portfolio optimizer does increase portfolio diversification for those investors that need diversification at the time they use the tool. Instead, the optimizer does not change the number of stocks held – or, if anything, it decreases it – for those investors that hold more than 30 stocks. These facts are consistent with the intuition that a crucial effect of the portfolio optimizer is the increase in diversification of the individual investors that use it.

6.3 Robo-advising and Trading Activity and Performance

We move on to assess the change in trading activity and performance by those investors that use the robo-advising tool. In particular, we consider three variables: (i) the change in the overall amount of fees each investor pays after adopting the tool compared to before, which captures investors' overall trading activity (top right panel of Figure 2); (ii) the change in the risk-adjusted returns of the stocks investors purchased after adoption compared to before, which captures investors' trading performance (bottom right panel of Figure 2); and (iii) the change in the number of logins in one's online account, which captures the change in investors' attention to their own portfolio after usage of the optimizer (bottom left panel of Figure 2). For all three variables, the pre- and post-periods are defined as three months before and after the first usage of the portfolio optimizer, respectively.

The right panels of Figure 2 show that the performance of the trades investors place after adopting the robo-advisor is economically and statistically higher than the performance before adoption for investors that held less than 5 stocks before adoption. These investors are those that increase the diversification of their portfolios after adoption. These are also the investors that do not face any significant increase in the fees they pay, which suggests that they place a similar number of trades and/or trades of similar size as they used to do before using the optimizer.

The patterns are quite different for investors that held more than 10 stocks before adopting the portfolio optimizer. These investors – which did not increase the diversification of their portfolio after using the optimizer, given they were already diversified – do not improve the market-adjusted returns of their trades after adoption. Moreover, they pay substantially higher fees, which suggests they place more trades and/or trades of larger size, compared to before using the optimizer.

Overall, the data described so far suggests that the robo-advising tool has a substantially different impact on investors, depending on the level of diversification of their portfolios before adoption. Highly underdiversified investors – those holding less than 5 stocks – diversify their portfolios substantially more after adoption, start to place trades that perform better than those they placed before adoption, and gain in performance without a significant change in the amount of fees they pay. Although these preliminary results do not allow for a complete assessment of the costs and benefits of adopting the optimizer tool, they suggest that underdiversified investors might gain from adopting the tool.

We detect a very different pattern for investors that were already diversified before adopting the robo-advising tool. These investors either do not change or decrease the number of stocks they hold, and pay substantially higher fees after adoption. These preliminary results seem to suggest that investors that were already diversified before the introduction of the robo-advising tool might, if anything, lose from adopting it.

Interestingly, variables that capture investors' attention to their portfolios, such as the number of logins to online accounts, increased substantially both economically and statistically after adoption of the tool for *all* investors, irrespective of their level of diversification. All investors paid more attention to their portfolios after adoption, but their reactions depended on the level of diversification before adoption.

To further assess the extent to which adopting the robo-advising tool affected investors' holdings, we test for the "extensive margin" of the effects, that is, the share of investors that changed their portfolio holdings within each category, based on their ex-ante diversification.

Figure 3 reports the results for this analysis. The left y-axis measures the share of investors that increase the number of stocks they hold after adoption compared to before, for each of the 5 groups sorted by the number of stocks investors held before adoption. This axis is associated with the solid, black line. The right y-axis measures the share of investors that decrease the number of stocks they hold after adoption compared to before. The right y-axis is associated with the dashed, red line.

The picture shows that the extensive margins of the increase and decrease of stock holdings after adoption of the robo-advising tool are in line with the intensive-margin analysis described above. On the one hand, the share of investors that increase their stock holdings after the adoption of the robo-advising tool is about 70% among the investors that held less than 2 stocks before adoption. This share decreases monotonically the higher the number of shares held before adoption, and is about 50% for investors that held more than 10 stocks before adoption. On the other hand, the share of investors that decrease the number of stocks they hold after adoption is less than 5% of those that held less than 3 stocks before adoption. This share increases monotonically, and reaches 30% among the investors that held more than 30 stocks after adoption.

6.4 Robo-advising and Behavioral Biases

The analysis of trading behavior and trading performance shows that investors that were diversified before using the optimizer pay higher fees in the 3 months after usage of the optimizer. This result might stem from the fact that these investors place more trades than before using the optimizer, that they place larger trades, or both. The portfolio optimizer might therefore exacerbate any behavioral biases that might affect investors.

To assess this possibility, we plan on performing the set of analyses described in Section 5.2 using a set of measures of behavioral biases as our outcome variables. In particular, we plan on measuring the disposition effect, the home bias, and the tendency of stock purchases to underperform stock sales, which the literature has interpreted as evidence of excessive trading on the part of individual investors.

As of today, we have analyzed the tendency of purchases to perform worse than sales. In untabulated results, we find that this tendency appears to increase after usage of the portfolio optimizer, especially for investors that were diversified before usage, which are those placing more – and worse – trades after using the optimizer.

7 Timeline of Delivery

Our original proposal has benefited substantially from the comments we obtained from two anonymous referees during the first stage of the procedure, both in terms of the focus and direction of the paper, as well as on the specific tests and analyses to run. We plan on having a completed draft of the paper by September 30th, 2017.

References

Aghion, P., and P. Howitt. 1992. A model of growth through creative destruction. *Econometrica* 60:323–51.

Anagol, S., V. Balasubramaniam, and T. Ramadorai. 2017. Endowment effects in the field: Evidence from india's ipo lotteries. *Unpublished Working Paper* .

Atkin, D., A. Chaudhry, S. Chaudry, A. K. Khandelwal, and E. Verhoogen. 2015. Organizational barriers to technology adoption: Evidence from soccer-ball producers in pakistan. Tech. rep., National Bureau of Economic Research.

Badarinza, C., J. Y. Campbell, and T. Ramadorai. 2016. International comparative household finance. *Annual Review of Economics* 8:111–44.

Barber, B. M., and T. Odean. 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies* 21:785–818.

———. 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The journal of Finance* 55:773–806.

Barberis, N., and R. Thaler. 2003. A survey of behavioral finance. *Handbook of the Economics of Finance* 1:1053–128.

Bold, T., K. C. Kaizzi, J. Svensson, and D. Yanagizawa-Drott. Forthcoming. Lemon technologies and adoption: Measurement, theory and evidence from agricultural markets in uganda. *The Quarterly Journal of Economics* .

Calvet, L. E., J. Y. Campbell, and P. Sodini. 2009. Fight or flight? portfolio rebalancing by individual investors. *The Quarterly journal of economics* 124:301–48.

Campbell, J. Y. 2006. Household finance. *The Journal of Finance* 61:1553–604.

Campbell, J. Y., and L. M. Viceira. 2002. *Strategic asset allocation: portfolio choice for long-term investors*. Oxford University Press, USA.

Chandra, A., A. Finkelstein, A. Sacarny, and C. Syverson. 2016. Health care exceptionalism? performance and allocation in the us health care sector. *The American economic review* 106:2110–44.

Chari, V. V., and H. Hopenhayn. 1991. Vintage human capital, growth, and the diffusion of new technology. *Journal of political Economy* 99:1142–65.

Comin, D., and M. Mestieri. 2014. Technology diffusion: Measurement, causes, and consequences. In P. Aghion and S. N. Durlauf, eds., *Handbook of Economic Growth*, vol. 2 of *Handbook of Economic Growth*, 565 – 622. Elsevier.

Conley, T. G., and C. R. Udry. 2010. Learning about a new technology: Pineapple in ghana. *American Economic Review* 100:35–69.

Dupas, P. 2014. Short-run subsidies and long-run adoption of new health products: Evidence from a field experiment. *Econometrica* 82:197–228.

Dupas, P., and J. Robinson. 2013. Why don't the poor save more? evidence from health savings experiments. *The American Economic Review* 103:1138–71.

Frame, W. S., and L. J. White. 2004. Empirical studies of financial innovation: lots of talk, little action? *Journal of Economic Literature* 42:116–44.

Frydman, C., S. M. Hartzmark, and D. H. Solomon. Forthcoming. Rolling mental accounts. *Review of Financial Studies* .

Gennaioli, N., A. Shleifer, and R. Vishny. 2015. Money doctors. *The Journal of Finance* 70:91–114.

Griliches, Z. 1957. Hybrid corn: An exploration in the economics of technological change. *Econometrica* 501–22.

Grinblatt, M., and M. Keloharju. 2001a. How distance, language, and culture influence stockholdings and trades. *The Journal of Finance* 56:1053–73.

———. 2001b. What makes investors trade? *The Journal of Finance* 56:589–616.

Jovanovic, B., and S. Lach. 1997. Product innovation and the business cycle. *International Economic Review* 38:3–22.

Jovanovic, B., and Y. Nyarko. 1996. Learning by doing and the choice of technology. *Econometrica* 64:1299–310.

Linnainmaa, J. T., B. T. Melzer, and A. Previtero. 2016. The misguided beliefs of financial advisors. *Working Paper* .

Logg, J. M. 2017. Theory of machine: When do people rely on algorithms? *Working Paper* .

Manuelli, R. E., and A. Seshadri. 2014. Human capital and the wealth of nations. *The American Economic Review* 104:2736–62.

Odean, T. 1998. Are investors reluctant to realize their losses? *The Journal of finance* 53:1775–98.

———. 1999. Do investors trade too much? *American Economic Review* 89:1279–98.

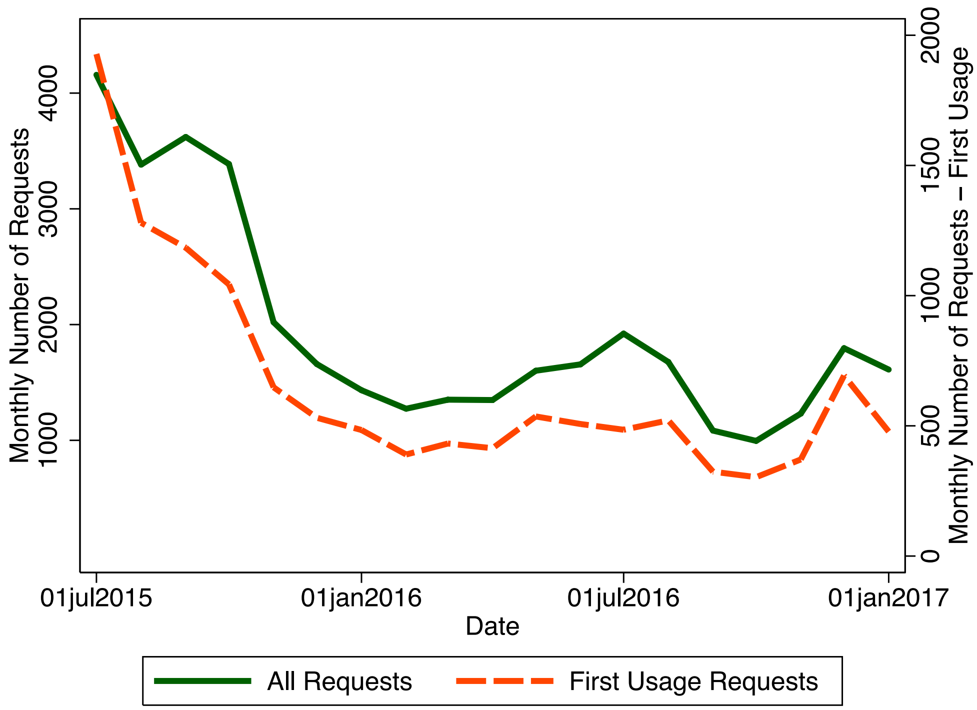
Romer, P. M. 1990. Endogenous technological change. *Journal of political Economy* 98:S71–S102.

Skinner, J., and D. Staiger. 2015. Technology diffusion and productivity growth in health care. *Review of Economics and Statistics* 97:951–64.

Solow, R. M. 1956. A contribution to the theory of economic growth. *The quarterly journal of economics* 70:65–94.

Tufano, P. 1989. Financial innovation and first-mover advantages. *Journal of Financial Economics* 25:213–40.

Figure 1: Number of Individual Requests to Use the Portfolio Optimizer over Time



This figure plots the overall number of requests to use the portfolio optimizer by all the brokerage house clients (solid line, left y-axis), as well as the requests to use the portfolio optimizer for the first time (dashed lines, right y-axis), for each week between July 1st 2015 – when the tool was first introduced to the clients of the brokerage house – and January 2017.

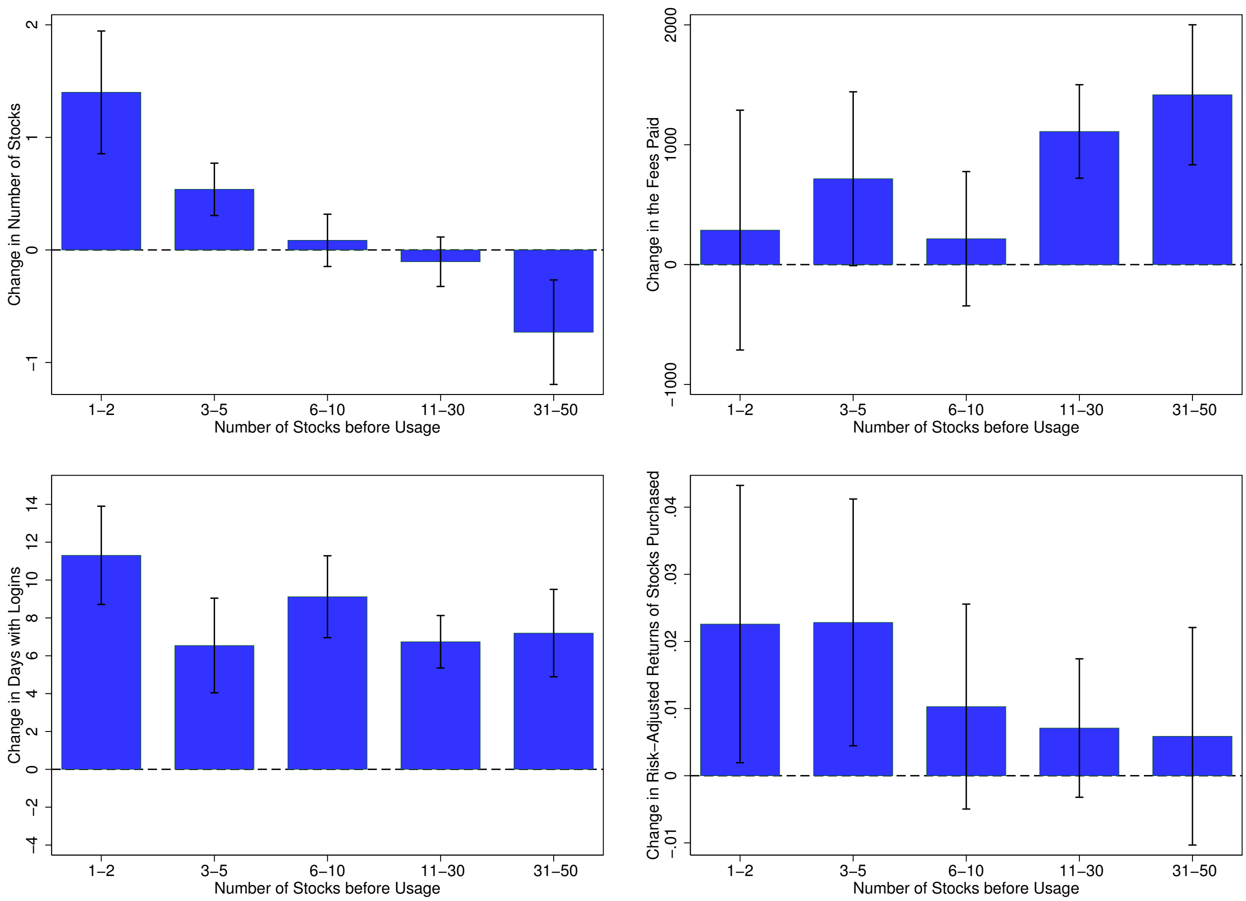


Figure 2: Trading Behavior and Performance Before and After Robo-advising

This figure documents the change in trading behavior and performance by investors that use the portfolio optimizer, before and after usage. In all panels, investors are sorted on the x-axis based on the number of stocks they held before using the robo-advising tool. As for the y-axes, in the top left panel we report the change in the number of stocks investors hold in their portfolios one month after usage compared to one month before usage. In the top right panel, we report the change in the overall amount of fees investors paid three months after usage compared to three months before usage. In the bottom-right panel, we report the change in the average 3-month market-adjusted returns of trades placed in the three months after usage, compared to those for the trades placed in the three months before usage. In the bottom-left panel, we report the change in the number of days in which investors logged into their online accounts over the three months after usage, compared to the three months before usage. Bars refer to the point estimate of the average values within each category of investors. The vertical segments represent 90% confidence intervals for the true mean values within each category of investors.

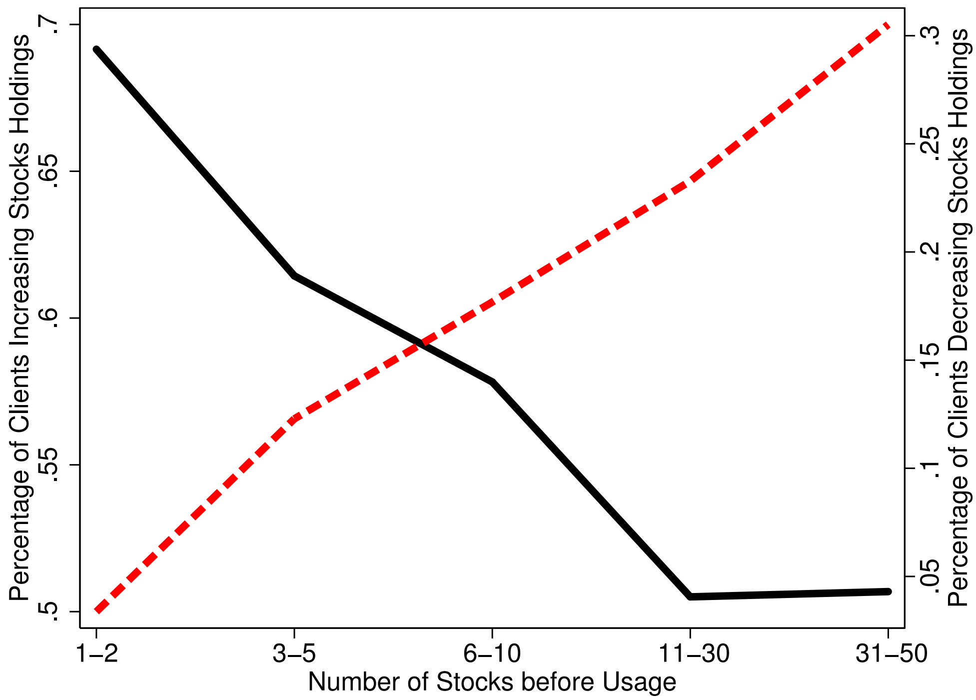


Figure 3: Investors that Increase and Decrease the Number of Stocks Held After Robo-advising

This figure documents the extensive-margin changes in the number of stocks held after usage of the robo-advising tool. The x-axis sorts investors based on the number of stocks they held before using the robo-advising tool. The left y-axis is associated with the solid, black line. It reports the fraction of investors within each group, who increased the number of stocks held over the three-month period after the first usage of the robo-advising tool, compared to the three months before usage. The right y-axis is associated with the dashed, red line. It reports the fraction of investors within each group, who decreased the number of stocks held over the three-month period after the first usage of the robo-advising tool, compared to the three months before usage.

Table 1. Demographic Characteristics

A. All Accounts

	Obs	**Mean**	**St.Dev**	**p.1**	**p.25**	**p.50**	**p.75**	**p.99**
Age	860,943	47.30	13.63	20.73	36.72	45.80	56.80	82.17
Male	838,364	0.75	0.44	0.00	0.00	1.00	1.00	1.00
Account Age	880,254	7.41	3.68	0.12	5.16	8.44	10.12	13.21

B. Accounts with at Least One Trade

	Obs	**Mean**	**St.Dev**	**p.1**	**p.25**	**p.50**	**p.75**	**p.99**
Age	265,538	46.26	14.14	19.21	35.12	45.02	56.53	80.60
Male	258,656	0.71	0.46	0.00	0.00	1.00	1.00	1.00
Account Age	265,310	5.83	3.96	0.21	1.94	6.08	9.27	13.08

C. Accounts with Holdings Information

	Obs	**Mean**	**St.Dev**	**p.1**	**p.25**	**p.50**	**p.75**	**p.99**
Age	282,795	48.28	13.32	21.79	38.01	47.28	57.73	81.15
Male	274,048	0.72	0.45	0.00	0.00	1.00	1.00	1.00
Account Age	283,323	7.64	3.27	1.33	5.53	8.38	10.11	13.10

D. Accounts with Logins Information

	Obs	**Mean**	**St.Dev**	**p.1**	**p.25**	**p.50**	**p.75**	**p.99**
Age	138,482	41.52	13.30	16.98	31.37	38.84	50.35	76.59
Male	136,330	0.74	0.44	0.00	0.00	1.00	1.00	1.00
Account Age	138,405	4.06	3.75	0.12	0.92	2.29	7.04	12.86

E. Accounts that Use the Portfolio Optimizer

	Obs	**Mean**	**St.Dev**	**p.1**	**p.25**	**p.50**	**p.75**	**p.99**
Age	12,714	48.00	14.49	17.02	36.54	47.10	59.03	81.14
Male	12,386	0.71	0.45	0.00	0.00	1.00	1.00	1.00
Account Age	12,706	6.01	4.09	0.28	1.88	6.06	9.61	13.08

This table presents summary statistics of the demographic characteristics in our datasets. For each variable in each panel, we report the total number of observations (*Obs*), the sample mean ($Mean$), the sample standard deviation ($St.Dev$) and the 1*st*, 25*th*, 50*th*, 75*th* and 99*th* percentiles of the distributions. Panel A considers all account holders. Panel B considers only those accounts that have traded once over the period April 2015 – January 2017. Panel C considers only account holders for which we have holdings information over the period January 2016 – January 2017. Panel D considers account holders for which we have logins information over the period April 2015 – January 2017. Finally, Panel E considers account holders that use the portfolio optimizer over the period July 2015 – January 2017.

Table 2. Portfolio Characteristics and Investment Behavior: Non-Users Vs Users of the Portfolio Optimizer

A. Demographic Characteristics

	Non-Users				Users			
	Obs	**Mean**	**St.Dev**	**Median**	**Obs**	**Mean**	**St.Dev**	**Median**
Age	254,273	46.19	14.13	44.92	11,265	47.81	14.48	46.87
Male	247,674	0.71	0.46	1	10,982	0.71	0.45	1
Account Age	254,053	5.83	3.95	6.09	11,257	5.81	4.09	5.54

B. Attention and Trading Behavior

	Non-Users				Users			
	Obs	**Mean**	**St.Dev**	**Median**	**Obs**	**Mean**	**St.Dev**	**Median**
Total Logins	98,771	432.85	844.19	84	7,310	657.87	1,020.29	220
Total Trades	254,281	122.38	339.03	15.00	11,265	186.47	398.57	45
Total Volume (₹ 000)	254,281	5,992	19,181	323	11,265	10,599	25,979	1,196
Total Fees (₹ 000)	254,281	10.07	27.43	1.09	11,265	17.69	37.03	3.58

C. Trading performance

	Non-Users				Users			
	Obs	**Mean**	**St.Dev**	**Median**	**Obs**	**Mean**	**St.Dev**	**Median**
Returns Buys (1m)	205,484	-1.22	5.52	-1.11	10,468	-0.86	4.10	-0.86
Returns Sells (1m)	237,395	-0.67	6.38	-0.96	10,797	-0.42	4.81	-0.71
Returns Buys (3m)	201,413	-3.60	10.33	-3.29	10,378	-2.55	7.61	-2.42
Returns Sells (3m)	232,449	-2.54	11.66	-2.77	10,666	-1.79	8.70	-2.22

D. Holdings as of January 1st 2016

	Non-Users				Users			
	Obs	**Mean**	**St.Dev**	**Median**	**Obs**	**Mean**	**St.Dev**	**Median**
Total AUM	165,983	434,149	1,210,555	72,476	9,327	1,107,550	2,054,217	313,195
Number of Assets	165,983	9.52	12.48	5	9,327	17.27	16.79	12
AUM Stocks	160,402	411,997	1,157,347	68,317	9,208	1,032,630	1,946,557	284,572
Number of Stocks	160,402	9.30	12.27	5	9,208	16.43	16.35	11
AUM Bonds	19,175	141,315	510,280	2,722	2,099	194,415	639,247	5,813
Number of Bonds	19,175	1.61	1.32	1	2,099	1.84	1.64	1
AUM Funds	30,390	78,726	212026	11,890	2,413	125,968	270,957	31,710
Number of Funds	30,390	1.58	1.33	1	2,413	1.97	1.62	1
AUM ETF	8,522	54,158	104,577	18,502	921	63,073	10,9765	22,801
Number of ETFs	8,522	1.19	0.46	1	921	1.30	0.57	1

This table reports summary statistics of the demographic characteristics (Panel A), attention and trading behavior (Panel B), the trading performance (Panel C) and the portfolio holdings (Panel D) of the brokerage account holders in our datasets. In each panel, the results for those that do not use the portfolio optimizer are reported in columns 2 through 5, while the results for those that use the portfolio optimizer at least once are reported in columns 6 through 9. For each variable in each panel, we report the total number of observations (*Obs*), the sample mean (*Mean*), the sample standard deviation (*St.Dev*) and the sample median (*Median*). The results in panels A through C are computed over the full sample, while the results in Panel D are computed as of January 1^{st} 2016.