The Promises and Pitfalls of Robo-advising

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PRELIMINARY DRAFT

Abstract

We study a robo-advising portfolio optimizer that constructs tailored strategies based on investors' holdings and preferences. Adopters are similar to non-adopters in terms of demographics, but have more assets under management, trade more, and have higher risk-adjusted performance. The robo-advising tool has opposite effects across investors with different levels of diversification before adoption. It increases portfolio diversification and decreases volatility for those that held less than 5 stocks before adoption. These investors' portfolios perform better after using the tool. At the same time, robo-advising barely affects diversification for investors that held more than 10 stocks before adoption. It increases the fees they pay, but not their performance. For all investors, robo-advising reduces – but does not fully eliminate – pervasive behavioral biases such as the disposition effect, trend chasing, and the rank effect, and increases attention based on online account logins. Our results inform the optimal design of robo-advising tools, which are becoming ubiquitous all over the world.

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1 Introduction

Most investors would benefit from stock market participation because of the high risk premia in stock markets (Campbell (2006) and Campbell and Viceira (2002)). 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 underdiversified. Financial advising can potentially help mitigate underdiversification, nudge investors towards more diversified portfolios, and thus help investors realize better outcomes. At the same time, financial advisers 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. The crucial difference between robo-advising tools like the one we study and earlier forms of unbiased advice proposed in the literature (e.g., see Bhattacharya et al. (2012)) is that robo-advising includes an *automatic*, simple, and immediate procedure investors can use to implement the advice they receive – investors merely need to click on a button to execute a large set of trades in batch mode. Instead, earlier forms of unbiased advice had extremely low compliance rates – especially among those in higher need of advice – possibly because acting on advice is too complicated for such investors. The result is ineffectiveness of the advice. As Bhattacharya et al. (2012) suggest, "you can lead a horse to water, but you can't make it drink." Robo-advising aims at making it extremely simple for non-financially-savvy investors to implement financial advice.

Our 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. Users and non-users are indistinguishable along several demographic characteristics, including their gender, age, and trading experience. At the same time, users have a larger amount of wealth invested with the brokerage house. They also appear to be more directly involved with the management of their portfolios as they login more frequently to their online accounts, and call their advisers more often than non-users. Finally, users appear to be more sophisticated. Their trades have superior risk-adjusted performance compared to non-users.

The robo-advising tool we study 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-adviser 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 thousands 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 use suboptimal rules of thumb (e.g., see Frydman, Hartzmark, and Solomon, Forthcoming). The robo-advising tool helps by reducing the multi-dimensional portfolio problem investors face into a simple decision.

We first analyze the effects of robo-advising on portfolio diversification, risk, and investment returns in a within-investor analysis, which partials out all the time-invariant determinants of adoption. A successful robo-adviser should increase the diversification of those investors that were the least diversified before using the tool. Consistently, 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 doubles 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 10 stocks. The effect becomes negative for investors that held more than 10 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. Moreover, portfolio volatility decreases substantially for those holding 10 stocks or less before adoption, whereas it barely changes for those holding more than 11 stocks before adoption. These 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 different levels of diversification across investors before usage. This result emphasizes the importance of robo-advising in making action simple for investors, and hence allowing the *least* financially savvy to improve their investment outcomes, different from other forms of unbiased financial advice (Bhattacharya et al. (2012)).

We move on to assess the effects of the usage of the portfolio optimizer on trading performance and trading behavior, based on investors' levels of diversification before usage. We find that all investors increase the number of trades they place after using the portfolio optimizer. But the market-adjusted trading performance of the ex-ante underdiversified investors improves after using the optimizer, in terms of both trade and portfolio performance. Instead, 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. These results suggest that on average using the tool benefits ex-ante underdiversified investors, but not investors that were already diversified before adoption.

Third, we study the extent to which adopting the robo-advising tool affects a set of well-documented biases attributed to individual investors. On the one hand, the trades suggested by the robo-advising tool should not reflect any behavioral biases.[1] A reduction in the extent of behavioral biases could therefore be mechanical or could stem from the fact that investors learn how to place unbiased trades as they follow the robo-advising tool, and might start to place unbiased trades even absent the use of the optimizer. On the other hand, because investors trade more after using the robo-advising tool, the effects of behavioral biases could be higher if investors increased the number of trades they placed without a direct recommendation by the robo-adviser.

[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) Because robo-advising algorithms are designed by humans, these algorithms might themselves reflect the behavioral biases of those designing them.

We focus on three well-documented biases, that is, (i) the disposition effect, whereby investors are more likely to realize gains than losses on their positions; (ii) trend chasing, whereby investors tend to purchase stocks after a set of positive returns with the expectations that positive returns will be more likely than negative returns going forward; and (iii) the rank effect, whereby investors are more likely to sell the best performing and worst performing stocks in their portfolios, compared to the other stocks. We find that all three biases are substantially less pronounced after the usage of the portfolio optimizer, irrespective of investors' level of diversification before usage. At the same time, the tool does not fully debias investors.

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

At the same time, the single-difference tests do not allow us to address a set of confounding explanations for our results. 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 she wants to trade more, and might think using the portfolio optimizer will give her ideas on which trades to place and how much to invest. Moreover, an underdiversified investor might realize she needs to hold more stocks, and might use the portfolio optimizer to get ideas on which additional stocks to purchase, but she might have purchased more stocks even if the optimizer was not available.

To address these identification issues, we propose a strategy that exploits the quasi-random variation of the likelihood that otherwise similar investors use the portfolio optimizer on the same day. We build on the fact that the brokerage house asked their human advisers at several points in time to call their clients to promote the usage of the portfolio optimizer and help them use the tool for the first time. The brokerage house had no underlying motivations for pushing the usage of the portfolio optimizer at any point in time, apart from the fact that their technology team thought the device was ready to use broadly and they wanted to market it as a free service to their clients.

Crucially, we observe all the outbound and inbound calls human advisers have with clients at each point in time. Moreover, we know whether calls went through and, if yes, the length of each call. We can therefore construct a treated and a control sample of clients as follows. Treated clients are those clients the human advisers reached in the days in which they were promoting the portfolio optimizer, and which indeed used the optimizer that day during the call with their adviser. Control clients are all those clients that the human advisers *tried* to contact on the same day to promote the optimizer, but who did not answer the phone, and hence did not have the chance to hear the adviser promoting the tool and helping them use it.[2]

This strategy helps us address the issue that clients might decide to change their trading behavior because of time-varying shocks to trading motives, and would have changed their behavior even absent the option of using the optimizer.

Note that the list of clients advisers call among the set of clients they oversee is not random. Advisers might call clients whose characteristics make them more likely to adopt the optimizer, or clients they think would benefit the most from using the optimizer. But this potential selection is not a problem for our strategy, because the clients that do not answer the phone would be chosen by advisers based on their likelihood of using and/or benefiting from the optimizer exactly as the clients that answer the phone.

Moreover, one might be worried that our strategy estimates the causal effect of human advisers suggesting clients they should change their investment strategies, as opposed to the effect of the robo-advising on clients' investment behavior and performance. This concern is barely relevant in our case, because advisers contact clients frequently with their own advice regarding clients' strategies even in days in which they are not promoting the portfolio optimizer. If human advice was relevant, it should affect clients irrespective of the use of the portfolio optimizer, and hence we should detect no effects of the adoption of the robo-advising tool.

Overall, our baseline results are confirmed when we restrict the analysis to comparing clients that used the portfolio optimizer after talking to their advisers in days in which the advisers were promoting the tool with clients that were contacted the same day by advisers but for which the call did not go through, and hence did not use the optimizer.

Overall, our results are among the first that study the effects of robo-advising on investors' holdings and performance. Specifically, we are the first that study the heterogeneity of the effects of robo-

[2] We require that non-responsive clients did not use the portfolio optimizer in the thirty days after the attempted call by their human adviser. The results are not sensitive to using different horizons for this restriction.

advising on different types of investors, based on their diversification before adopting the technology. These results can inform the optimal design of robo-advising tools, and provide direction about which types of investors would benefit from adopting robo-advising technologies, and which types of investors would not necessarily benefit from it.

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 considerably 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

[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.

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 Robo-Advising

Our paper tests the effects of one robo-adviser on individual investors' financial decisions. While very similar in nature, robo-advisers vary in sophistication and – potentially – in their effectiveness. In this section, we classify the robo-advisers that populate the market and provide a summary of their characteristics.

Most robo-advisers exploit Markowitz (1952)'s mean-variance optimization. The primary benefit of mean-variance optimization is portfolio diversification. While the expected returns on a given portfolio are the weighted average of the expected returns of the individual assets, the risk of the portfolio is lower than the weighted average risk of the individual assets as long as assets are not perfectly positively correlated. It is thus possible to both increase the expected returns and reduce the risk of a relatively under-diversified portfolio by adding assets to the portfolio and choosing their portfolio weights optimally.

Despite its undeniable influence on the asset management industry, mean-variance optimization has a number of limitations. As a one-period model, mean-variance optimization does not consider time variation in the investment opportunity set. Neither does it consider explicitly that the efficient frontier is a function of each individual investor's horizon. The framework also assumes that returns are jointly normally distributed, while substantial empirical evidence shows returns are significantly

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

fat-tailed. Implementation also faces several challenges. Estimating variance-covariance matrices would require long samples to reduce estimation error. At the same time, assets display time-varying correlation, making it hard to determine the optimal estimation window. A standard way to reduce the effect of estimation error is to use shrinkage (e.g., see Ledoit and Wolf (2004)), or Bayesian techniques (e.g., see Black and Litterman (1991)). Short-selling constraints are also common.

The majority of operators in the robo-advising space do not disclose the details of their portfolio allocation strategies. Even the three most popular robo-advisers in US – Schwab Intelligent Portfolios, Wealthfront, and Betterment – do not provide detailed information on how their algorithms are designed. For example, Schwab does not provide any information on how they compute the variances and covariances of their model. On its website, Wealthfront claims they use both historical stock-market data and options data. Betterment uses the Black-Litterman approach, combined with the shrinkage proposed in Ledoit and Wolf (2004).

Robo-advisers also differ substantially in the number of asset classes they include in their optimization. Schwab considers the broadest set of asset classes among the three. The asset classes they consider include US and international equities, US and international treasuries and corporate bonds , TIPS, municipal bonds, and gold. Wealthfront and Betterment are narrower in that they focus mainly on US stocks and bonds. Once the optimal portfolio is selected, the strategies are generally implemented using ETFs, which are liquid, can be traded at low costs, and have a rather small tracking error.

Robo-advisers are generally considered a significant improvement over human financial advisers for a number of reasons. First, robo-advisers are grounded on financial theory. Human advisers, on the other hand, might be subject to a wide array of behavioral biases they pass on to their clients (e.g., see (Linnainmaa, Melzer, and Previtero, 2016)). Mullainathan, Noeth, and Schoar (2012) also show that human advisers tend to recommend actively-managed mutual funds as opposed to passive index funds. Second, robo-advisers are more transparent than human advisers. Robo-advisers propose an allocation and the investor decides whether to move to the suggested allocation. The interaction between human advisers and clients, on the other hand, resembles a sales transaction, in which the adviser has an incentive to cater to the investors' biases and misconception to gain his/her trust. Few human advisers provide advice before the clients' wealth has been transferred to the adviser. Finally, robo-advisers are likely to be more efficient in implementing tax-loss harvesting strategies compared to human advisers.

On the other hand, robo-advisers have been criticized for putting company profits ahead of investors' interests. For example, Schwab Intelligent Portfolios have been criticized for allocating too much for their investors' portfolios in cash. The underlying motive might be that Schwab deposits the cash at Schwab Bank to lend it at a profit. Schwab has also been criticized for implementing the investment strategies using Schwab ETFs that have higher expense ratios compared to competing ETFs.

3.1 The Robo-advising Tool We Study

The robo-advising technology we study – named *Portfolio Optimizer* – focuses on equities only and 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 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.

The robo-adviser we analyze has several limitations compared to the popular robo-advisers marketed in the US. First, it focuses only on equities and implements the recommendation using individual stocks rather than ETFs. Second, while it imposes short-sales constraints and operates shrinkage on the estimated variances and co-variances, it uses only three years of data for estimation. Although US-based robo-advising companies do not report the horizon of the data they use, the three years used by our optimizer might deliver unstable excess return estimates. The optimizer is also likely to overweigh *momentum stocks* that have appreciated substantially over the previous years in the proposed portfolio. Finally, no strict rule exists to identify the 15 additional stocks the optimizer considers to add to the investor's portfolio upon usage.

The robo-adviser we analyze is similar to the Portfolio Visualizer marketed in the US by Silicon Cloud Technologies,[5] and is specifically catered to investors that are interested in selecting individual securities, rather than holding ETFs. By revealed preferences, the clients of the firm we analyze are interested in holding individual stocks. When the firm introduced the optimizer, their objective was to provide an automated alternative to the human advisers that interact with clients on a regular basis. The goal of our analysis is to study the extent to which an optimizer like the one we consider might help investors' portfolio allocation despite its limitations.

[5] For further information, see `https://www.portfoliovisualizer.com`

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 massive round of advertising and marketing of the tool to their clients. On top of these company-wide promotion campaigns, the company asked each day different advisers to contact their clients and promote the use of the portfolio optimizer. 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 adviser 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 adviser 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 Selection into the Adoption of Robo-advising

In the first part of our analysis, we study the selection of individual investors into adopting the robo-advising technology. To do this, we perform a simple cross-sectional comparison across two groups of clients of the brokerage house, that is, users and non-users. We start from the raw data, and we restrict the analysis to the sample of investors that place at least one trade during our sample period. We compare the demographic characteristics of investors that adopt and do not adopt the robo-advising tool at any point in time since July 2015 – when the brokerage house first introduced the tool. Moreover, we describe the cross-sectional variation of the trading performance and holdings of investors that do and do not adopt the tool.

Because we compare characteristics across users and non-users irrespective of the timing of usage, and hence pooling together the periods before and after the use of the portfolio optimizer, the cross-sectional variation described below cannot be interpreted as the effects of using the portfolio optimizer on investors' trading behavior or invested wealth. This variation captures 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.

Panel A of Table 2 compares 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. 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 Adoption of Robo-advising, Trading Behavior, and Performance

In the second part of the analysis, we study the effects of using the robo-advising tool on investors' holdings, trading behavior and trading performance. In this section, we restrict the sample to investors that use the portfolio optimizer at any point in time since July 2015. For those that use the optimizer more than once, we only consider the first date of usage of the optimizer.[6] Our baseline design for this analysis is a single-difference approach, in which we compare investors' 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 can drive any variation in trading behavior and performance we might observe in the data.

6.1 Robo-advising and Portfolio Diversification

The first set of outcomes we consider are diversification outcomes, that is, the number of stocks investors hold in their portfolios as well as the volatility of their portfolios.

Table 3 reports the average change in a set of portfolio-level outcomes before and after usage of the portfolio optimizer, and across all investors in our sample. Panel A reports the average change in the number of the stocks (column (1)) and in the market-adjusted portfolio volatility (column (2)). In column (1), we find that on average investors increase the number of stocks they hold by 0.16 units, which is about 1.3% of the median number of stocks investors held before using the portfolio optimizer (12 stocks).

Pooling together all investors masks substantial variation of the baseline effects in the cross-section, especially based on the extent of diversification before using the optimizer. Table 2 highlights large cross-sectional variation in the average number of stocks held by investors in our sample before using the optimizer. Some investors are underdiversified – e.g., they only hold 1 or 2 stocks – whereas other investors hold a large number of stocks. 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

[6] The median user of the portfolio optimizer uses it once.

of stocks. If anything, the optimizer might set some optimal weights to zero because of short-sale constraints. Based on this conjecture, we would expect that the number of stocks held increases for underdiversified investors after using the optimizer, and portfolio volatility decreases for them, whereas both dimensions do not change for investors that were diversified before using the optimizer.

To assess the effect of the portfolio optimizer on diversification conditional on the extent of diversification before usage, we first 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 4 groups of investors, based on the number of stocks they held before usage.

The top panel of Figure 2 reports the results of this exercise. 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 4 groups based on the number of stocks they held before using the optimizer. We report 90% confidence intervals around the estimated means.

Consistent with the conjecture described above, the association between the pre-usage number of stocks and the 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. This group of investors increases the size of the portfolio by about 100% on average. The effect is positive both economically and statistically also for those holding between 3 and 5 stocks and between 6 and 10 stocks, but the estimated magnitudes of the change decrease significantly the higher the number of stocks held. Finally, the change becomes negative and statistically significant for those holding more than 10 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.

We move on to assess the effects of using the portfolio optimizer on the market-adjusted risk of investors' portfolios. Market adjusted risk is the difference between portfolio realized volatility and market realized volatility at the monthly level, both computed using daily data. In column (2) of Table 3, we consider all investors. We find that on average market-adjusted portfolio volatility decreases by 2.07% per year.[7]

[7] We annualize the coefficient in column (2) multiplying it by $\sqrt{12}$.

Again, the average result across all investors masks substantial heterogeneity based on the ex-ante levels of diversification. In the bottom panel of Figure 2, each bar represents the change in the market-adjusted risk of investors' portfolios across our 4 groups of investors sorted based on the number of stocks they held before using the optimizer. Consistent with the results on the change in the number of stocks held, we uncover a monotonic pattern whereby abnormal portfolio volatility decreases substantially for investors that held 1 or 2 stocks before using the optimizer. The extent of the decrease in volatility is significantly lower for investors that held between 3 and 5 stocks, and it is even lower for investors that held more than 5 stocks. Note that whereas investors that were diversified ex ante decrease the number of stocks held, their market-adjusted risk does not increase, which suggests that the portfolio optimizer increases portfolio diversification also for those that were already diversified ex ante.

To further assess the extent to which adopting the robo-advising tool affected investors' holdings, we consider 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 4 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, blue line.

Figure 3 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 38% among the investors that held less than 3 stocks before adoption. This share decreases monotonically the higher the number of shares held before adoption, and is about 22% 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 about 5% of those that held less than 3 stocks before adoption. This share increases monotonically, and reaches 24% among the investors that held more than 10 stocks after adoption.

Overall, the within-investor single-difference 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 10 stocks. Consistently, market-adjusted portfolio volatility decreases substantially for ex-ante less diversified investors, and this decrease declines monotonically with the number of stocks investors held before using the optimizer.

6.2 Robo-advising, Investment Performance, and Trading Activity

We move on to assess the extent to which the investment performance and trading activity of the investors that use the robo-advising tool changes after usage, compared to before. As far as investment performance is concerned, we consider both market-adjusted portfolio performance and the market-adjusted returns of individual trades. For trading activity we consider the overall amount of brokerage fees investors pay, which is proportional to their number of trades, and the amount of attention investors allocate to their portfolios, as proxied by the number of days with logins to their online brokerage accounts.

Panel B of Table 3 reports the average change in investors' market-adjusted trade performance (column (1)) and market-adjusted portfolio performance (column (2)). In both cases, the average change is positive, although we can reject the null that the coefficient equals zero at plausible levels of significance only for the market-adjusted portfolio performance.

Figure 4 shows the estimation separately across groups of investors, based on the number of stocks they held before using the optimizer. We find the same patterns for average trade performance (top panel) and average portfolio performance (bottom panel). In both cases, performance improves significantly for the investors that held less than 3 stocks before using the optimizer, and hence that were highly underdiversified before usage. At the same time, performance does not change significantly, either economically or statistically, for any of the other groups of investors. These results emphasize the positive effects of adopting the robo-advising tool especially for highly underdiversified investors, which we have discussed in the previous section.

As far as trading activity is concerned, in Panel C of Table 3 we report the average change across all investors in the overall amount of brokerage fees investors pay after using the optimizer (column (1)) and the overall number of days with logins to their online brokerage accounts (column (2)). On average, monthly fees increase by 155 rupees, which is about 15% of the average amount of fees investors paid in the month before using the optimizer (1,000 rupees). Moreover, on average users of the portfolio optimizer login to their online account for 10 days in the month before adoption, and we find that on average they increase this figure by 1 day, which is 10% of the average effect.

When we split the set of investors based on ex-ante diversification, we find again substantial heterogeneity in the size of effects across groups. The top panel of Figure 5 shows that trading fees only increase significantly, both economically and statistically, for investors that were already diversified before using the portfolio optimizer. Thus, investors that were already diversified before using the optimizer did not increase their diversification or their performance, but at the same time increased the number of trades and hence the amount of fees paid.

When we split the effect of using the optimizer on the number of days with logins, we find that all investors pay more attention to their portfolios, irrespective of the number of stocks held before using the optimizer (see the bottom panel of Figure 5).

Overall, the results described so far suggest that the robo-advising tool has a 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, which decreases their market-adjusted portfolio volatility. They also 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 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.

Interestingly, variables that capture investors' attention to their portfolios, such as the number of logins to online accounts, increased 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.

6.3 Robo-advising and Behavioral Biases

The last set of outcomes we study relates to a set of well-documented biases attributed to individual investors by earlier research. On the one hand, the trades suggested by the robo-advising tool should not reflect any behavioral biases.[8] On the other hand, because investors trade more after using the robo-advising tool, the effects of behavioral biases could be higher if investors increased the number of trades they placed without a direct recommendation by the robo-adviser.

We focus on three well-documented behavioral biases of individual investors, that is, (i) the disposition effect, whereby investors are more likely to realize gains than losses on their positions; (ii) trend chasing, whereby investors tend to purchase stocks after a set of positive returns with the expectations that positive returns will be more likely than negative returns going forward; and (iii) the rank effect, whereby investors are more likely to sell the best performing and worst performing stocks in their portfolios, compared to the other stocks. We find the three biases are substantially less pronounced for all investors after usage of the portfolio optimizer, irrespective of their level of diversification before usage. At the same time, the tool does not fully debias investors.

6.3.1 Disposition Effect (Gambler's Fallacy)

The disposition effect is the tendency by individual investors to realize gains more often than losses (e.g., Odean (1998)). To measure the extent of disposition effect in our sample, we follow Odean (1998) and compute the difference between the proportion of gains realized (PGR) and the proportion of losses realized (PLR) for each investor before and after using the portfolio optimizer, where:

$$PGR = \frac{Realized\ Gains}{Realized\ Gains + Paper\ Gains}$$

$$PLR = \frac{Realized\ Losses}{Realized\ Losses + Paper\ Losses}.$$

Investors display a disposition effect if PGR>PLR. Moreover, the larger the positive difference between PGR and PLR, the more severe the disposition effect the investor displays. The disposition effect is an example of *gambler's fallacy*: investors sell gaining stocks because they expect gaining stocks to lose going forward; at the same time, investors do not want to sell losing stocks because they expect them to rebound and gain more going forward.

[8] 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) Because robo-advising algorithms are designed by humans, these algorithms might themselves reflect the behavioral biases of those designing them.

The top left panel of Figure 6, each bar represents the difference between PGR and PLR as defined above. The bar to the left is the average difference across portfolio optimizer users before usage, whereas the bar to the right is the average difference after usage. Two results are apparent from the figure. First, the extent of disposition effect among investors decreases after they use the robo-advising tool, which suggests that the tool allows investors to decrease the extent of biases that affect them. At the same time, the difference between PGR and PLR is still statistically and economically greater than zero even after investors use the portfolio optimizer, which suggests that on average the robo-advising tool does not fully debias investors.

Comparing the confidence intervals around the estimated average effects, we see that the average difference PGR-PLR is significantly lower after using the portfolio optimizer compared to before using it. We also report a formal test for whether the difference PGR-PLR changes systematically before and after the use of the portfolio optimizer. In Table 4 panel A, we do reject the null that the difference equals zero both statistically and economically at conventional levels of significance.

To assess the economic magnitude of this change, we compare the size of the change to the extent of the bias the average investor displays before using the portfolio optimizer. The size of the difference between PGR and PLR before using the optimizer is about 2 percentage points in our sample. The size of the change of this difference after using the optimizer in Table 4 panel A is about 0.6 percentage points. Therefore, using the portfolio optimizer is associated with a drop in the extent of the disposition effect, as measured by the difference between the proportion of gains realized and the proportion of losses realized, by about 30%, which appears to be a significant economic magnitude.

The limited time span of our data does not allow us to test whether the effect of using the portfolio optimizer on the extent of investors' behavioral biases increases over time – for instance, because investors learn about their biases after understanding they should realize losses if needed – or whether this effect is a one-time shock to the extent of biases. If learning played any role in explaining our results, we might expect that over time the extent of detected behavioral biases would decrease even more than what our current results suggest.

To analyze whether the effects of the optimizer vary across users with different characteristics, we provide two extensions of the baseline results. First, we limit the analysis to those clients that display a positive disposition effect before using the optimizer. We sort these clients into four quartiles, from low incidence of bias to high incidence of bias. We then compute the percentage of clients for which the disposition effect improves – that it, its incidence *decreases* – after using the optimizer. Panel A of Figure 7 reports these percentages in the form of bars. Moving from left to right, the percentage of clients for which the disposition effect decreases moves from approximately 60% for those with a low incidence of the disposition effect to almost 85% for those with a high incidence of the disposition effect. The confidence intervals attached to each estimated percentage indicate that the effect increases monotonically.

To further analyze the heterogeneity of the effect across clients, we compute the change in disposition effect for each client. We then plot the distributions of the change in disposition effect separately for each group of clients by incidence of the disposition effect before using the optimizer. Panel B of Figure 7 displays these distributions. Each plot in Panel B reports the results for different investors. The main takeaways are two. First, across all distributions the mean and the mode are below zero. It is also apparent that, while the disposition effect becomes even stronger (i.e., more positive) for certain clients in each group, the distributions are highly asymmetric. The vast majority of the population lies in the negative domain, which suggests that the incidence of the disposition effect decreases for most investors after using the optimizer. Taking the clients with high disposition effect as an example, it is clear that very few investors worsen after using the portfolio optimizer. Investors that happen to increase their disposition effect experience only a very small positive change. Those that improve, on the other hand, experience a significant negative change in the incidence of the disposition effect.

In the second extension we limit the analysis to those clients that display a positive disposition effect before using the optimizer, and we sort them into four groups based of the number of stocks investors hold at the time of usage. The results reported in Panel A of Figure 8 show that the percentage of clients that experience a decrease in the incidence of their disposition effect is concentrated among the clients with up to five stocks: the percentages are 60% and 65% among the clients with 1-2 and 3-5 stocks, respectively. The effects are much less pronounced among customers with more than five stocks, for which the percentages are around 55%. The results in Panel A of Figure 8 are confirmed in Panel B of 8, which reports the distributions of the changes across the various groups. For the clients with up to five stocks, the distributions are skewed to the left and have a negative mean. The distributions for the clients with more than five stock are more symmetric.

6.3.2 Trend Chasing

As a second example of investor bias, we consider trend chasing, that is, investors' tendency to purchase stocks after a set of subsequent increases in price, which suggests that investors believe a stock's price is more likely to increase than to decrease after a set of increases.

To measure the extent of trend chasing by investors in our sample, we limit the sample to stocks investors purchase. For each purchased stock, we consider the 5 business days before the purchase date, and we compute the number of days with positive stock returns in this pre-purchase period. We compute the same metric for all stock purchases after investors use the portfolio optimizer:

$$Trend\ Chasing = \frac{Days\ Price\ Increase}{Days\ Price\ Increase + Days\ Price\ Decrease}.$$

The top right panel of Figure 6 plots the average number of days with price increases, both before using the portfolio optimizer (left bar) and after using the optimizer (right bar). We find that our investors are more likely to buy stocks that experienced a lower series of positive returns in the 5 business days before purchases.

We test formally that the difference between the number of days with price increases before and after the use of the portfolio optimizer is significantly negative in Table 4. In panel B, we reject the null that the within-investor difference equals zero at any standard level of significance.

Similar to our procedure for the disposition effect in the previous subsection, we assess the magnitude of the change in trend chasing by comparing it with the average extent of the bias before usage of the portfolio optimizer. The share of positive returns observed in the 5 days prior to purchase is about 2.45, whereas the size of the change after using the optimizer compared to before in Table 4 panel B is about 0.03. The extent of reduction in trend chasing is thus about 1.2%. The size of this effect appears to be substantially smaller than the effect of using the optimizer on the measure of the disposition effect we proposed in the previous subsection.

6.3.3 Rank Effect

The third bias we consider is the rank effect first documented in a sample of US investors by Hartzmark (2014). The rank effect is the tendency of investors to sell the best and the worst performing stocks in their portfolios, while ignoring stocks in their portfolios that display intermediate performance. To compute the extent of rank effect at the investor level, we follow Hartzmark (2014) and first compute the proportion of best-, worst-, and middle-performing stocks investors sell:

$$Best = \frac{Best\ Sold}{Best\ Sold + Best\ not\ Sold}$$

$$Worst = \frac{Worst\ Sold}{Worst\ Sold + Worst\ not\ Sold}$$

$$Middle = \frac{Middle\ Sold}{Middle\ Sold + Middle\ not\ Sold}.$$

For each investor, we then compute the differences $Best - Middle$ and $Worst - Middle$, both before and after usage of the portfolio optimizer. Under the rank effect, we expect that both differences are statistically different from zero.

In the bottom left panel of Figure 6, each bar refers to the average difference $Best - Middle$ in our sample, both before usage of the optimizer (left bar) and after usage of the optimizer (right bar). In the bottom right panel of Figure 6, each bar refers to the difference $Worst - Middle$, again both before (left) and after (right) usage of the optimizer. As far as the tendency to sell the best performing stocks more than other stocks is concerned, we find that this tendency is substantially higher before usage than after usage. Similar to the results on the disposition effect, although the extent of the bias decreases after usage of the optimizer, it does not completely fade.

Different from the tendency to sell the best performing stocks, we find that the tendency to sell the worst performing stocks more than the mid-performing stocks is quite limited in our sample. Because of this small baseline effect, we fail to detect any systematic differences in the sizes of the effects for the average investor before and after using the portfolio optimizer.

We confirm these results by testing formally that the change in the prevalence of the rank effect before and after the use of the portfolio optimizer is significantly negative in Table 4. In panel C, we reject the null that the within-investor difference of $Best\ Middle$ equals zero at the 1% levels of significance. To the contrary, in panel D we fail to reject the null that the within-investor difference of $Worst - Middle$ equals zero at any plausible level of significance.

In terms of magnitude of the effect, we note that the share of best performing stocks sold on average before using the optimizer is 22%, whereas the change in this share after using the optimizer compared to before (Table 4 panel C) is 5.7 percentage points, which amounts to about 26% of the average extent of bias. Similar to the disposition effect – of which the rank effect can be considered a special case – the extent to which the portfolio optimizer reduced the bias appears to be substantial.

Overall, the results on behavioral biases suggest that usage of the portfolio optimizer reduces the prevalence of well-known biases among individual investors, although these biases do not wash away completely after the robo-advising intervention.

7 Identification Strategy

All the results we have described so far are based on single-difference tests. A drawback with this empirical design is that it does not allow us to address a set of alternative explanations for our results. In particular, any within-individual change in behavior could be driven by unobserved time-varying shocks to investors' trading motives, which might cause both the usage of the optimizer and the observed change in trading behavior before and after usage.

For instance, an investor could decide 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. If the investor would not change her behavior without using the optimizer, the single-difference tests would still estimate the causal effect of the use of the optimizer on investment behavior. But if the investor would have changed her trading behavior had the optimizer being available or not, then our baseline results would be spurious. Similarly, an underdiversified investor might realize she needs to hold more stocks, and might use the portfolio optimizer to get ideas on which additional stocks to purchase. If the investor would have purchased more stocks irrespective of the availability of the optimizer, and she only used the optimizer to have some guidance, then again the single-difference results could be spurious.

To address these concerns, we propose an identification strategy that exploits the quasi-random variation of the likelihood that otherwise similar investors use the portfolio optimizer at the same point in time. We build on the fact that the brokerage house asked human advisers to call their clients to promote the usage of the portfolio optimizer and help them use the tool for the first time. The brokerage house had no underlying motivations for pushing the usage of the portfolio optimizer at any point in time, apart from the fact that their technology team thought the device was ready to use broadly and they wanted to market it as an free perk to their clients.

Crucially, we observe all the outbound and inbound calls human advisers have with clients at each point in time. Moreover, we know whether calls went through and, if yes, the length of each call. We can therefore construct a treated and a control sample of clients as follows. Treated clients are those clients human advisers reached in the days in which they were promoting the usage of the portfolio optimizer, and which indeed used the optimizer that day during the call with their adviser. Control clients are all those clients human advisers *tried* to contact on the same day to promote the optimizer, but who did not answer the phone, and hence did not have the chance to hear the adviser promote the tool.[9] This strategy helps us address the issue that clients might decide to change their trading behavior because of time-varying shocks to trading motives, and would have changed their behavior even absent the option of using the optimizer.

We exploit the source of variation described above in the following difference-in-differences design:

$$(\overline{Outcome}_{reached_t,\ post} - \overline{Outcome}_{reached_t,\ pre}) - (\overline{Outcome}_{missed_t,\ post}) - \overline{Outcome}_{missed_t,\ pre}), \quad (1)$$

where *Outcome* is each of the measures of portfolio diversification, trading performance, and trading activity we studied in section 6; $reached_t$ indicates investors that were reached by the human adviser on day t in which the adviser promoted the portfolio optimizer, and used the optimizer that day; $missed_t$ indicates investors that the human adviser tried to reach on the day in which he/she promoted the portfolio optimizer (t), but for which the call did not go through; *pre* and *post* refer to the average of each outcomes for the observed period before and after day t.

Our identification strategy translates into the null hypothesis that the quantity defined in (1) equals zero. The crucial identifying assumption this strategy requires for causal identification is that absent the usage of the portfolio optimizer, the trading activity and performance of investors that

[9]We require that non-responsive clients did not use the portfolio optimizer in the thirty days after the attempted call by their human adviser. The results are not sensitive to using different horizons for this restriction.

were reached on day t would have followed parallel trends with respect to the trading activity and performance of investors that were missed on day t. Under this assumption, missed investors represent a viable counterfactual for the trading activity and performance of contacted investors that used the portfolio optimizer on day t.

Note that the list of clients advisers called among the set of clients they oversee regularly is not random. Advisers might call clients whose characteristics make them more likely to adopt the optimizer, or clients they think would benefit the most from using the optimizer. But this potential selection is not a relevant concern for our strategy, and does not represent a threat to identification in this context. This is because under such selection, the clients the adviser missed on the portfolio-optimizer promotion day would have been chosen by the adviser based on their likelihood of using and/or benefiting from the optimizer, exactly as the clients the adviser was able to reach. Therefore, this type of selection would – if anything – help the econometrician as it would make the treated and control samples similar based on potential unobservable dimensions that determine their trading activity and performance, which the adviser can observe but the econometrician cannot observe.

An additional concern one might have with our strategy is that it might estimate the causal effect of human advisers suggesting clients they should change their investment strategies, as opposed to the effect of the robo-advising on clients' investment behavior and performance. In fact, this concern seems barely relevant in our case, because advisers contact clients frequently with their own advice regarding clients' strategies even in days in which they are not promoting the portfolio optimizer. If investors changed their behavior to follow human advisers' recommendations they would have changed their behavior in earlier occasions in which they interacted with their human advisers, and hence we should detect no effects of using of the optimizer.

We estimate the following linear equation by OLS:

$$Change\ Outcome_i = \alpha + \beta \times Treated_i + \epsilon_i, \tag{2}$$

where $Change\ Outcome_i$ is the difference of the average of each outcome we consider before and after the day in which the adviser tried to reach client i, and $Treated_i$ is an indicator for whether the advisor was able to reach investor i via phone and the investor used the portfolio optimizer that day.

In Table 5, we report the estimated coefficients $\hat{\beta}$ for the set of outcomes we discussed in section

6. Note that the size of the identification sample is lower than the size of the baseline sample. This difference is due to the fact that the identification sample is restricted to the investors advisers tried to reach in the day they promoted the robo-advising tool.

Across all panels, most of the results are qualitatively similar to our baseline results. Two exceptions stand out, though.

First, in column (1) of panel A the coefficient on the change in number of stocks is positive but not statistically different from zero for treated investors. As we saw in the baseline results, though, this coefficient mask dramatic differences in the size of the effect across investors, based on the extent of their ex-ante diversification. We find the same exact monotonic pattern in the identification sample. Figure 9 reports the estimated $\hat{\beta}$ separately for 4 groups of investors, based on the number of stocks they held before using the optimizer. We find that, in line with the baseline results, the number of stocks held increases significantly for treated investors that held less than 5 stocks before using the optimizer. At the same time, the change in the number of stocks is not different from zero for treated investors that held between 6 and 10 stocks, whereas the number of stocks decreases for investors that held more than 10 stocks before using the optimizer.

The second departure from the baseline result is the insignificant effect of using the robo-advising tool on the portfolio market-adjusted risk, which we report in column (2) of Table 5. In the baseline analysis, we found this effect was negative, whereas in the identification sample we fail to reject the null that the effect is zero, either statistically or economically. Moreover, this effect does not appear to vary systematically across groups of treated investors based on their ex-ante diversification.

Moving on to the identification results for behavioral biases, Table 6 reports the estimated difference-in-differences effects of using the portfolio optimizer on the biases of treated investors compared to control investors. We find that all the baseline results go through in the identification sample. Specifically, after using the portfolio optimizer, treated investors are less likely to display the disposition effect, less likely to display a trend-chasing behavior, and less likely to display the rank effect – although, similar to the baseline analysis, the rank effect is limited to the tendency to sell the best performing stocks in our sample.

8 Conclusions

We use a unique sample of individual brokerage accounts to propose one of the first assessments of the effects of using a robo-advising tool – a portfolio optimizer that makes action on advice simple and immediate – on investor performance and trading behavior, including well-documented behavioral biases.

The central message of the paper is that adopting the robo-advising tool has substantially different effects across investors based on their extent of diversification before adoption. Investors that are underdiversified before adoption increase their portfolio diversification in terms of both the number of stocks they hold in their portfolio and the market-adjusted volatility of their portfolio. Moreover, they display higher performance in terms of both market-adjusted trade returns and market-adjusted portfolio returns.

Instead, investors that are highly diversified before adoption do not change their diversification, whereas they increase substantially their number of trades, as proxied by the higher brokerage fees they pay. At the same time, their higher trading activity does not translate into better performance, either at the trade or at the portfolio levels.

The extent to which investors are subject to well-known behavioral biases such as the disposition effect, trend chasing, and the rank effect, is the only outcome that improves for all investors.

Because the vast majority of the investors in our sample is underdiversified and has not used the robo-advising tool yet, these differential results suggest that a broader application of the tool might improve trading activity and performance for a large amount of investors.

Overall, our results have implications for the design of robo-advising interventions, which are becoming ubiquitous all over the world. The results suggest that financial institutions should target underdiversified investors with robo-advising tools, whereas more sophisticated investors and more diversified investors might display lower fee-adjusted performance after using robo-advisers. Future research should dig deeper into the optimal design of robo-advising interventions that might be tailored to the needs of different categories of investors.

More broadly, our results suggest that robo-advising is no panacea to the unsatisfactory performance of individual investors. Despite the promises of robo-advising, several investors face its pitfalls.

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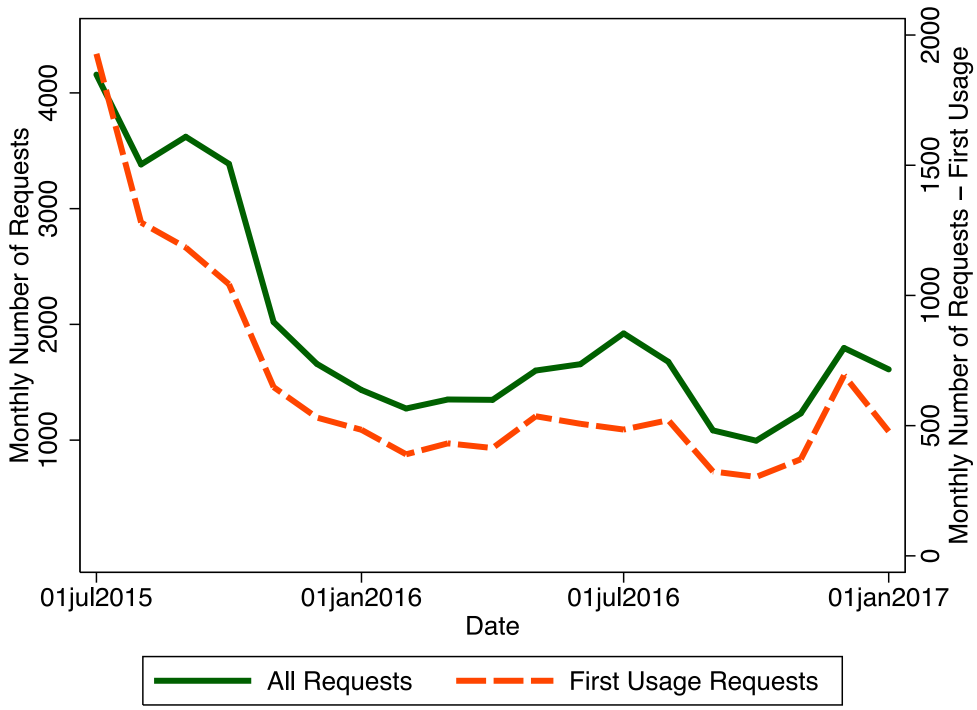


Figure 1: Number of Individual Requests to Use the Portfolio Optimizer over Time

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.

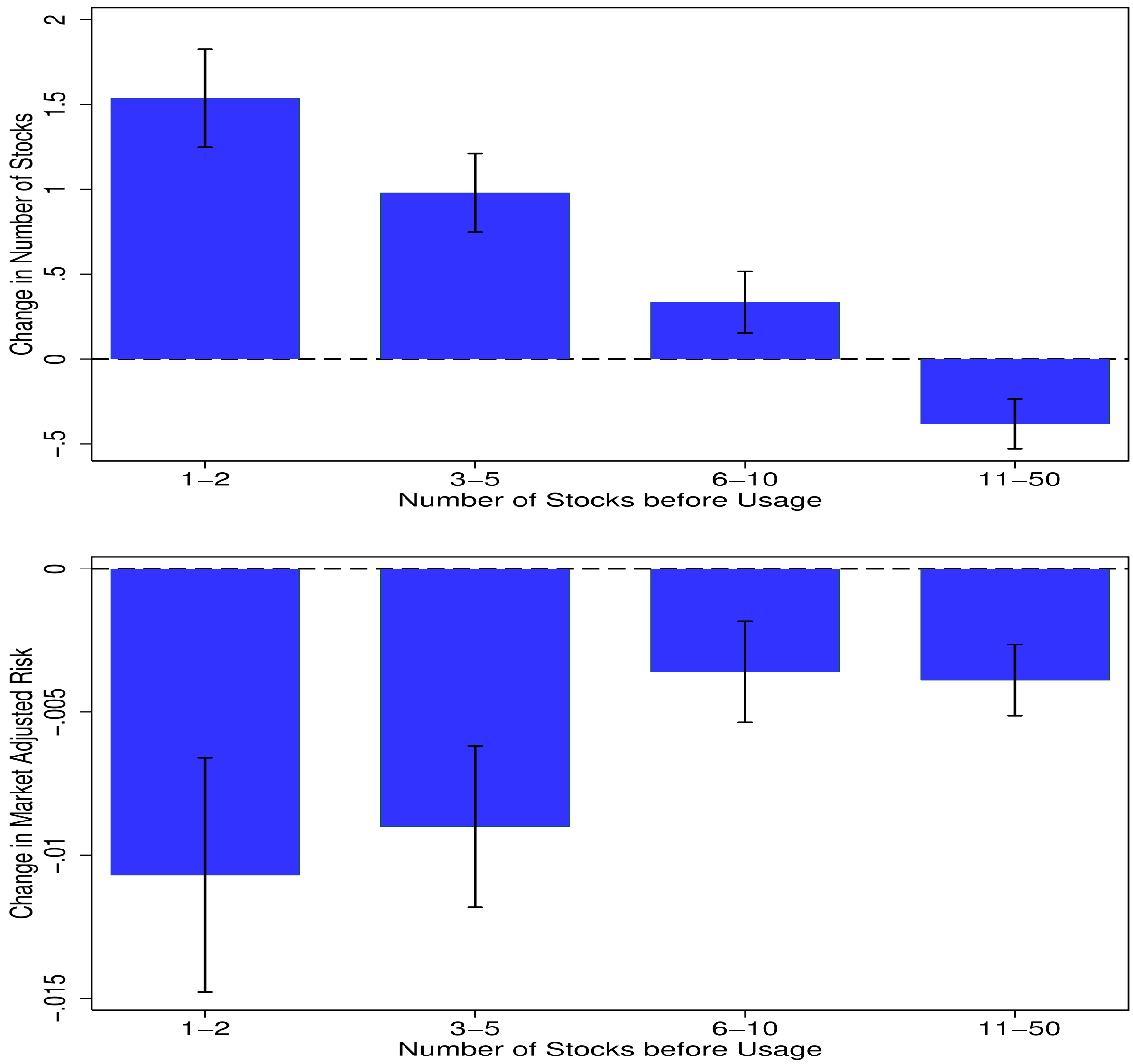


Figure 2: Portfolio Diversification and Risk Before and After Robo-advising

This figure documents the change in portfolio diversification and risk by investors that use the portfolio optimizer, before and after usage. In both 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 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 bottom panel, we report for the same groups the change in the market adjusted risk of the investors' portfolio. Market adjusted risk is the difference between portfolio realized volatility and market realized volatility at the monthly level, both computed using daily data. 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.

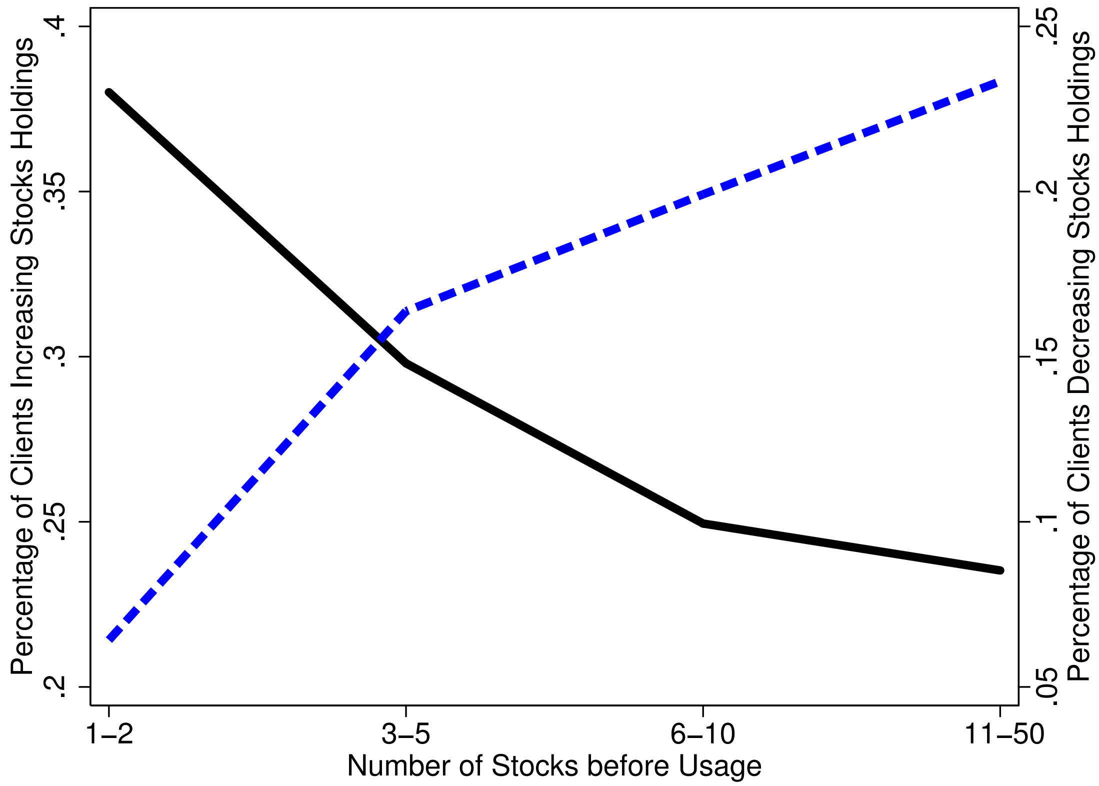


Figure 3: Investors that Increase and Decrease the Number of Stocks Held After Robo-advising

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 month after the first usage of the robo-advising tool, compared to the month before usage. The right y-axis is associated with the dashed, blue line. It reports the fraction of investors within each group, who decreased the number of stocks held over the month after the first usage of the robo-advising tool, compared to the month before usage.

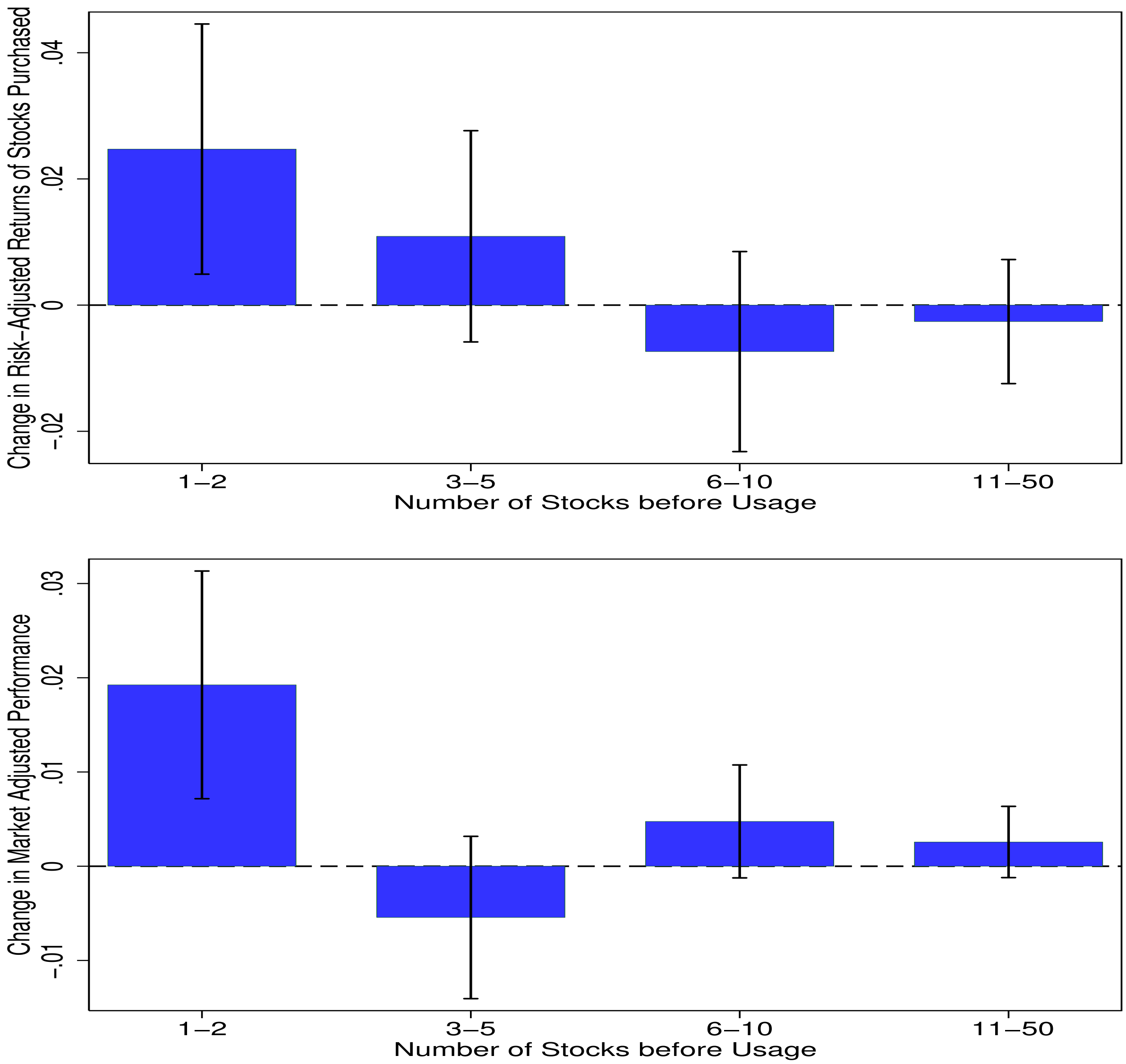


Figure 4: Investment Performance Before and After Robo-advising

This figure documents the change in investment performance at the individual trades and portfolio levels by investors that use the portfolio optimizer, before and after usage. In both 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 panel we report the change in the three-month risk-adjusted performance of the trades placed in the month after usage, compared to those for the trades placed in the month before usage. In the bottom panel, we report for the same groups the change in the market adjusted returns of the investors' portfolio. Market adjusted return is the difference between the investor portfolio return and the market return computed over one month. 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.

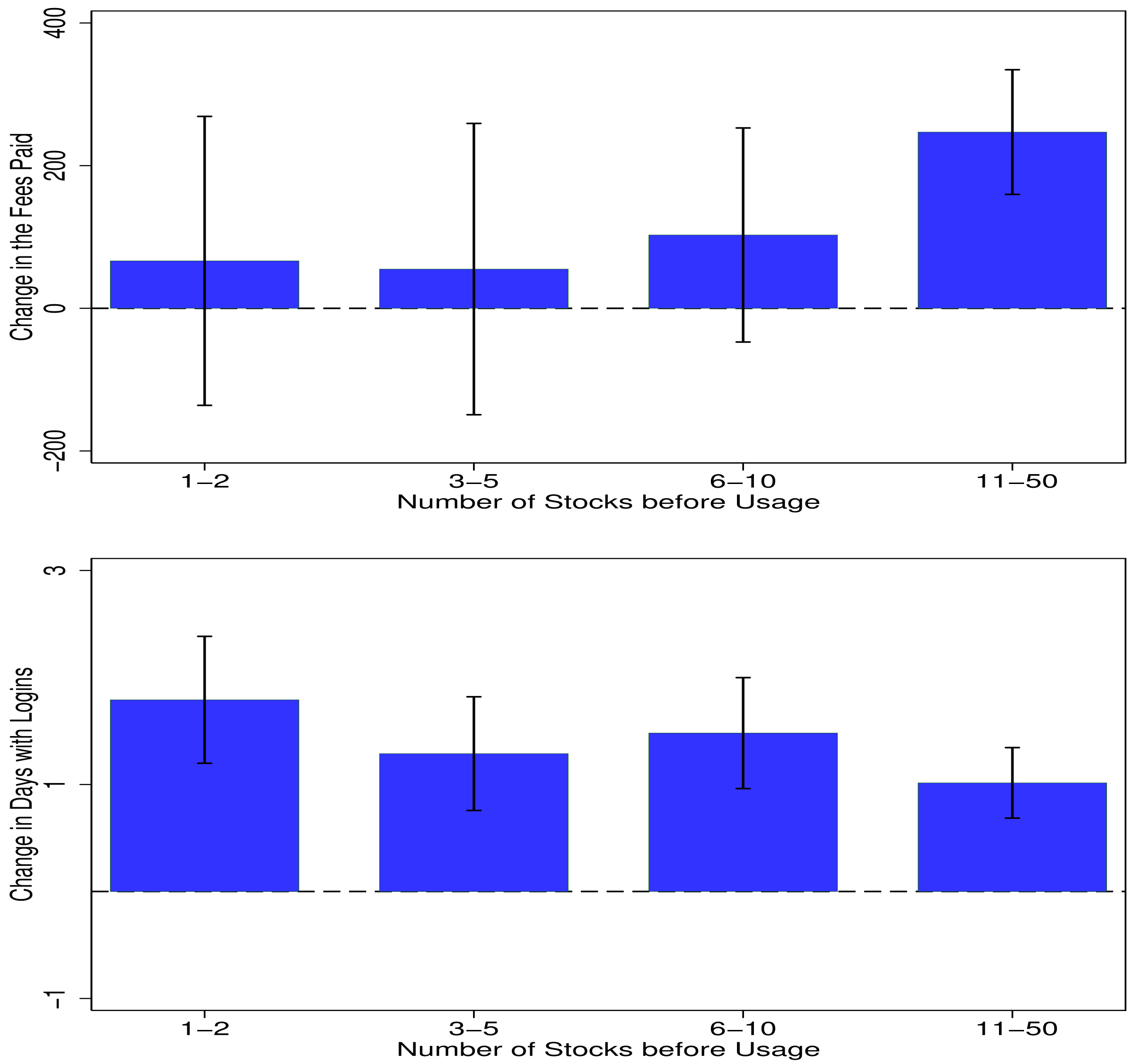


Figure 5: Trading Activity and Attention Before and After Robo-advising

This figure documents the change in trading activity and investor attention by investors that use the portfolio optimizer, before and after usage. In both 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 panel we report the change in the trading fees paid in the month after usage, compared to the trading fees in the month before usage. In the bottom panel, we report for the same groups the change in the number of days with logins in the month after usage, compared to the trading fees in the month 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.

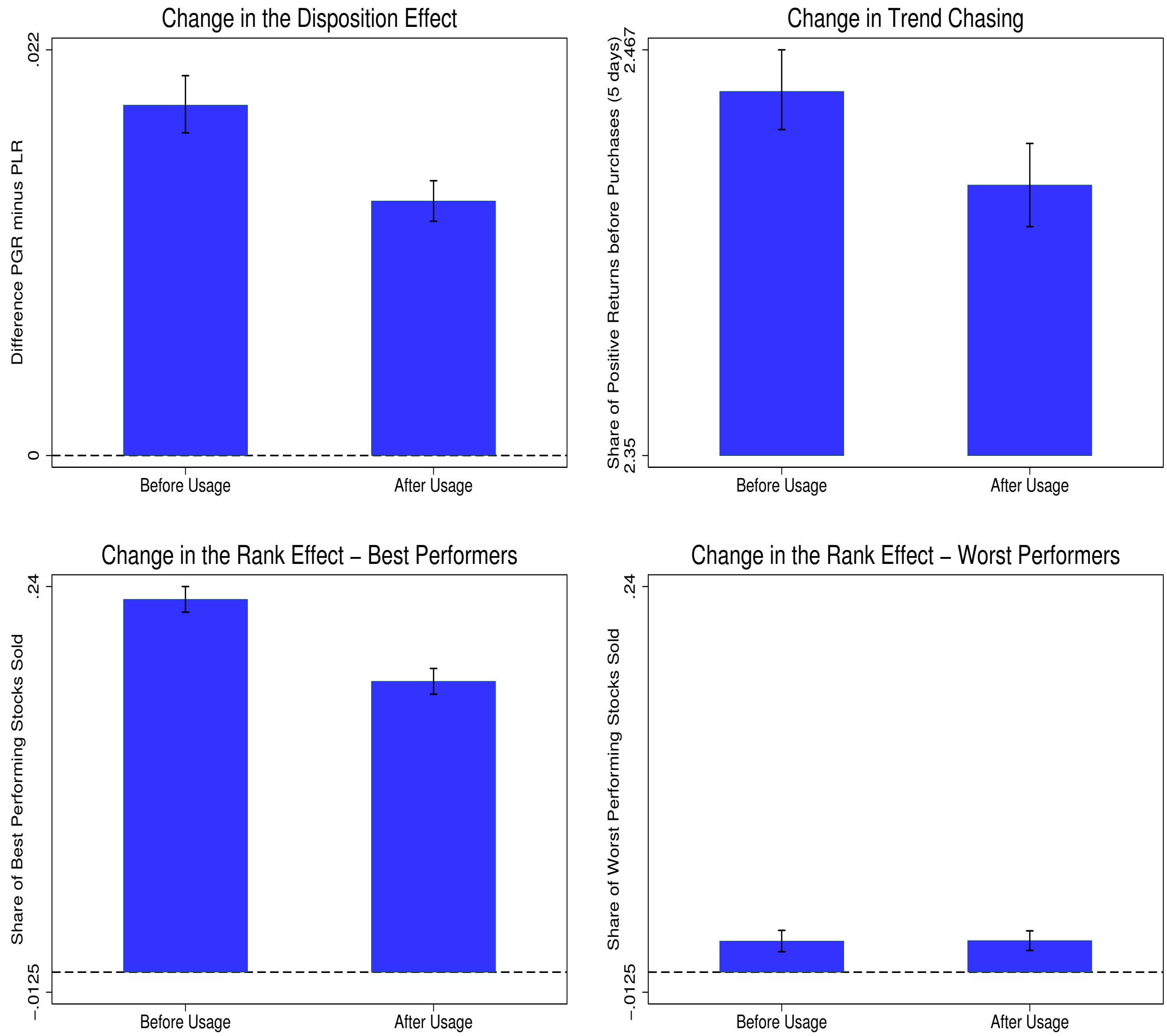
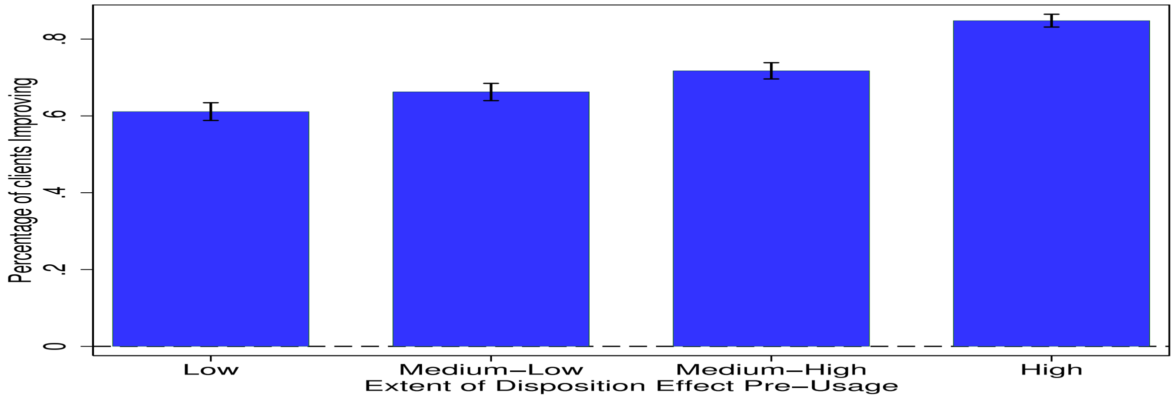


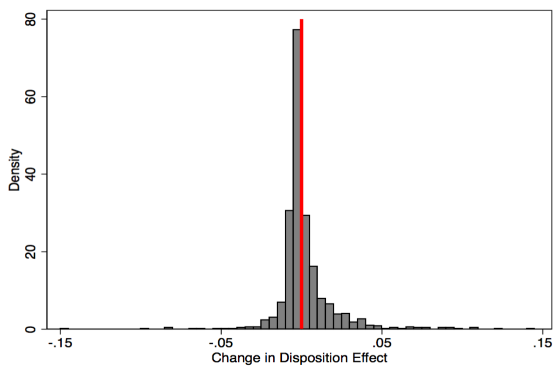
Figure 6: Behavioral Biases Before and After Robo-advising

This figure documents the change in behavioral biases by investors that use the portfolio optimizer, before and after usage. The top left panel reports the results for the disposition effect. Each bar is the average difference between the proportion of gains realized (PGR) and the proportion of losses realized (PLR) for each investor before and after using the optimizer. The top right panel reports the results for trend chasing. Each bar is the average number of days in which a stock purchased by the investor had positive daily returns among the 5 business days before the purchase. The bottom panels report the results for the rank effect for the best performing stocks in the investors' portfolio on the left and the worst performing stocks in the investors' portfolio on the right. Each bar is the average difference between the number of best/worst performing stocks sold and the number of mid-performing stocks sold before and after the use of the optimizer. The vertical segments are 90% confidence intervals for the true mean values within each category of investors.

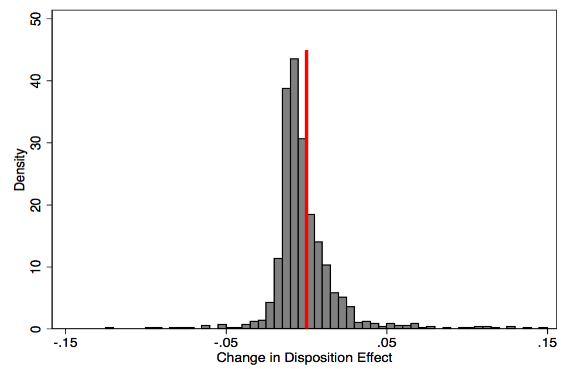
Panel A. Percentage of Clients Improving After Using the Optimizer:
Heterogeneity Across Investors on the Basis of their Disposition Effect Pre-Usage



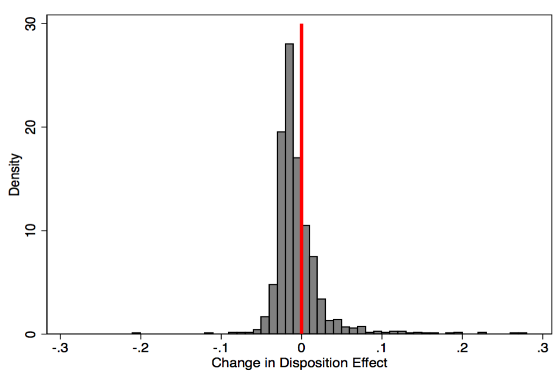
Panel B. Distributions of Changes in Disposition Effect After Usage of the Optimizer



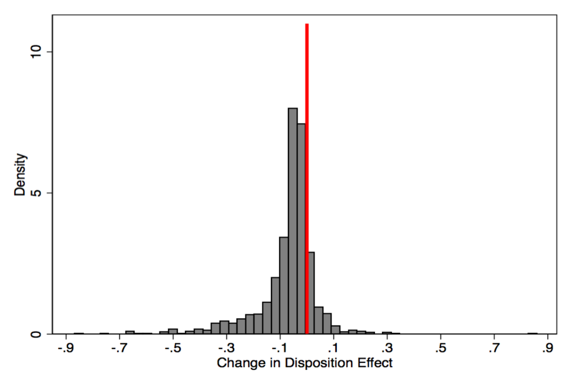
(a) Low Disposition Effect



(b) Medium-Low Disposition Effect



(c) Medium-High Disposition Effect

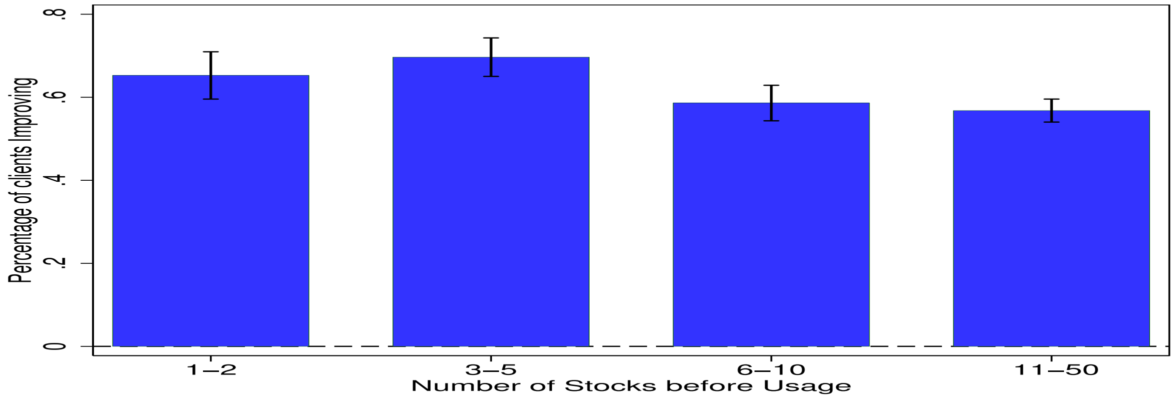


(d) High Disposition Effect

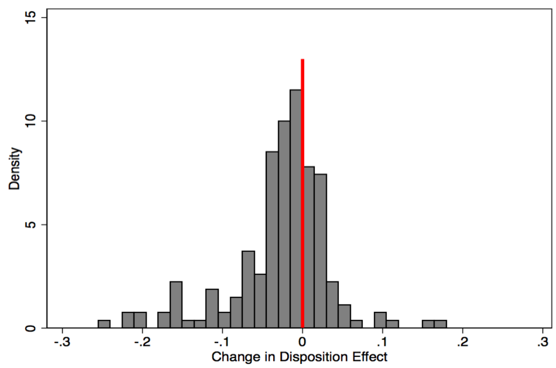
Figure 7: Disposition Effect Before and After Robo-advising, conditional on Bias Pre-Usage

This figure documents the change in the disposition effect for investors that use the portfolio optimizer, before and after usage, conditioning on the extent of the disposition effect before usage. The analysis includes only clients with a positive disposition effect before using the optimizer. These clients are sorted into four quartiles, from low to high disposition effect. Panel A reports the percentage of clients that experience an improvement in the disposition effect after usage by quartile. The vertical segments are 90% confidence intervals. Panel B computes the change in disposition effect for each client and presents the distribution of these changes by group.

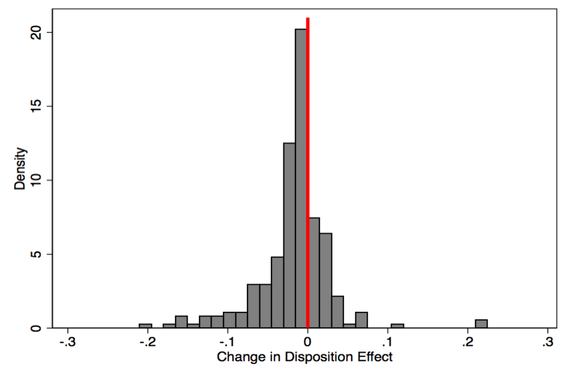
Panel A. Percentage of Clients Improving After Using the Optimizer:
Heterogeneity Across Investors with Different Number of Stocks Pre-Usage



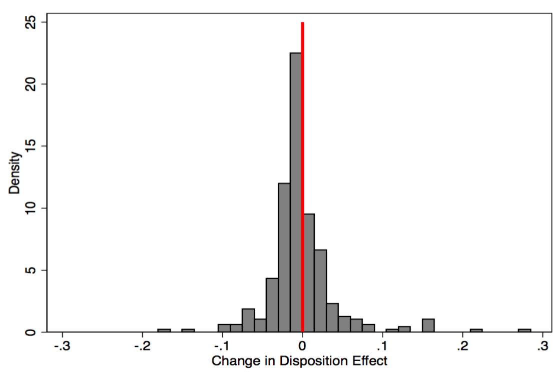
Panel B. Distributions of Changes in Disposition Effect After Usage of the Optimizer



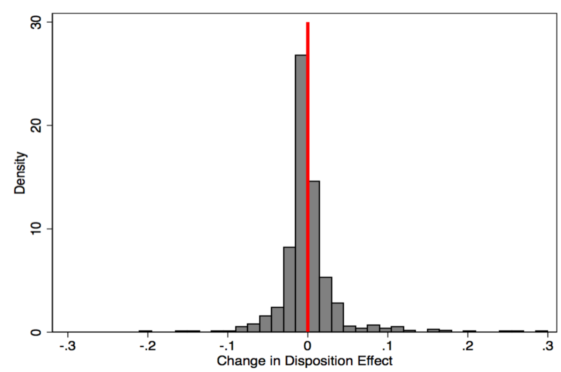
(a) Number of Stocks: 1-2



(b) Number of Stocks: 3-5



(c) Number of Stocks: 6-10



(d) Number of Stocks: 11-50

Figure 8: Disposition Effect Before and After Robo-advising, conditional on Number of Stocks

This figure documents the change in the disposition effect for investors that use the portfolio optimizer, before and after usage, conditioning on the number of stocks they hold before usage. The analysis includes only clients with a positive disposition effect before using the optimizer. These clients are sorted into four groups on the basis of the number of stocks they hold at the time they use the optimizier: 1-2 stocks, 3-5 stocks, 6-10 stocks and 11-50 stocks. effect. Panel A reports the percentage of clients that experience an improvement in the disposition effect after usage by group. The vertical segments are 90% confidence intervals. Panel B computes the change in disposition effect for each client and presents the distribution of these changes by group.

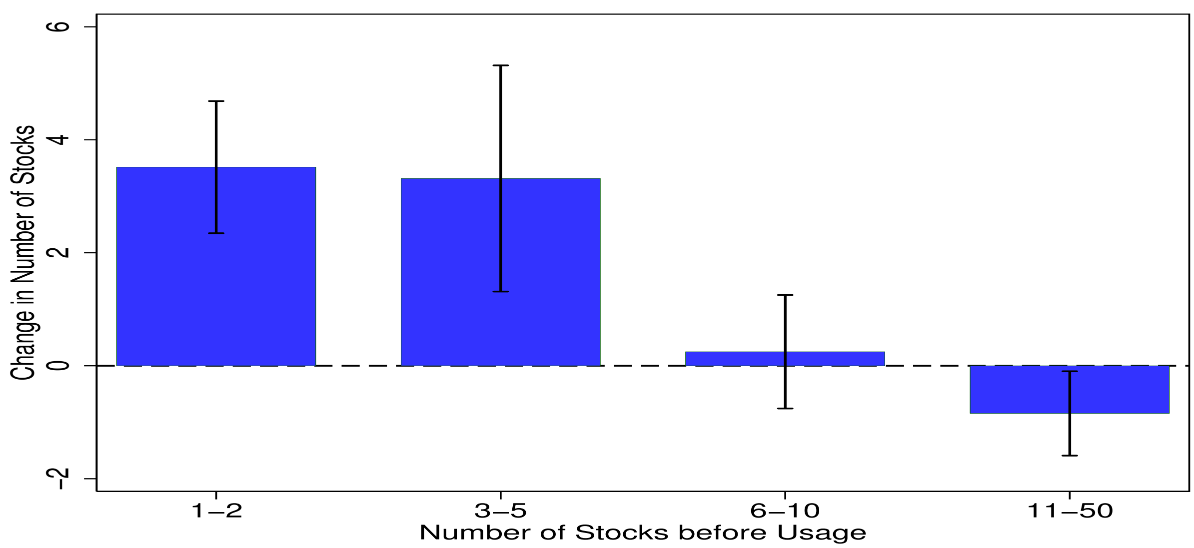


Figure 9: Identification Results: Number of Stocks and Portfolio Optimizer

This figure reports the identification results for the change in portfolio diversification by investors that use the portfolio optimizer, before and after usage, relative to those investors that were contacted on the same day by the same adviser, but did not answer the phone call. Investors are sorted on the x-axis based on the number of stocks they held before using the robo-advising tool. The y-axis reports the change in the number of stocks investors hold in their portfolios one month after usage compared to one month before usage – relative to the change for the control group. 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.

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 $1st$, $25th$, $50th$, $75th$ and $99th$ 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 (Rupee 000)	254,281	5,992	19,181	323	11,265	10,599	25,979	1,196
Total Fees (Rupee 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 1st 2016.

Table 3. Diversification, Attention and Trading Behavior Before and After Adopting the Portfolio Optimizer – Baseline Results

Panel A. Adoption of the Optimizer and Diversification

	Number of Stocks	Portfolio Market Adjusted Risk
Change after Adoption	0.156**	-0.006***
(p-value)	(0.04)	(0.02)
Obs	4,672	3,115

Panel B. Adoption of the Optimizer and Investment Performance

	Performance of Trades	Portfolio Market Adjusted Returns
Change after Adoption	0.003	0.005**
(p-value)	(0.47)	(0.02)
Obs	1,192	3,428

Panel C. Adoption of the Optimizer, Trading Activity and Attention

	Trading Fees	Days with Logins
Change after Adoption	155.4***	0.853***
(p-value)	(0.00)	(0.00)
Obs	6,594	4,000

This table reports results on investor behavior before and after adopting the portfolio optimizer. Panel A reports the changes in the number of stocks held (first column) and the market adjusted risk of the investor portfolio (second column). Panel B reports the changes in the risk-adjusted performance of the trades (first column) and the market adjusted performance of the investor portfolio (second column). Panel C reports the changes in the trading fees paid to the brokerage house (first column) and the number of days with logins (second column). All panels compare the behavior over the month after the usage and the behavior over the month before the usage. Each panel reports first-difference coefficients, the associated p-values and the number of observations.

Table 4. Behavioral Biases Before and After Adopting the Portfolio Optimizer – Baseline Results

	Panel A. Disposition Effect	Panel B. Trend Chasing Behavior
Change after Adoption	-0.006^{***}	-0.027^{***}
(p-value)	(0.00)	(0.00)
Obs	7,506	6,938
	Panel C. Rank Effect – Best	**Panel D. Rank Effect – Worst**
Change after Adoption	-0.057^{***}	0.007
(p-value)	(0.00)	(0.123)
Obs	4,264	4,264

This table tests whether the change in behavioral biases by investors that use the portfolio optimizer is different from zero before and after usage. Panel A reports the results for the disposition effect. *Change after Adoption* is the difference between the proportion of gains realized (PGR) and the proportion of losses realized (PLR) for each investor before and after using the optimizer. Panel B reports the results for trend chasing. *Change after Adoption* is the difference between the average number of days in which a stock purchased by the investor had positive daily returns among the 5 business days before the purchase, before and after adoption. Panel C and Panel D report the results for the rank effect. *Change after Adoption* is the average difference between the number of best/worst performing stocks sold and the number of mid-performing stocks sold before and after the use of the optimizer. Each panel reports first-difference coefficients, the associated p-values and the number of observations.

Table 5. Diversification, Attention and Trading Behavior Before and After Adopting the Portfolio Optimizer – Identification Results

Panel A. Adoption of the Optimizer and Diversification

	Number of Stocks	Portfolio Market Adjusted Risk
Treated	0.339	0.002
(p-value)	(0.37)	(0.65)
Obs	720	509

Panel B. Adoption of the Optimizer and Investment Performance

	Performance of Trades	Portfolio Market Adjusted Returns
Treated	0.004	0.031**
(p-value)	(0.68)	(0.01)
Obs	815	542

Panel C. Adoption of the Optimizer, Trading Activity and Attention

	Trading Fees	Days with Logins
Treated	318.9*	1.011***
(p-value)	(0.08)	(0.00)
Obs	1,507	1,086

This table reports the identification results for the change in portfolio diversification, trading activity, and performance by investors that use the portfolio optimizer, before and after usage, relative to those investors that were contacted on the same day by the same adviser, but did not answer the phone call. Treated is the estimated coefficient $\hat{\beta}$ from the following equation, which we estimate by OLS:

$$Change\ Outcome_i = \alpha + \beta \times Treated_i + \epsilon_i$$

Panel A reports results for the number of stocks held (first column) and the market adjusted risk of the investor portfolio (second column). Panel B reports the changes in the risk-adjusted performance of the trades (first column) and the market adjusted performance of the investor portfolio (second column). Panel C reports the changes in the trading fees paid to the brokerage house (first column) and the number of days with logins (second column). All panels compare the behavior over the month after the usage and the behavior over the month before the usage. For each difference-in-differences coefficient we report the associated p-value and the number of observations in the regression.

Table 6. Behavioral Biases Before and After Adopting the Portfolio Optimizer – Identification Results

	Panel A. Disposition Effect	Panel B. Trend Chasing Behavior
Treated	-0.008^{***}	-0.069^{***}
(p-value)	(0.00)	(0.00)
Obs	2,766	2,752
	Panel C. Rank Effect – Best	**Panel D. Rank Effect – Worst**
Treated	-0.058^{***}	-0.006
(p-value)	(0.00)	(0.27)
Obs	2,621	2,621

This table reports the identification results for the change in behavioral biases by investors that use the portfolio optimizer, before and after usage, relative to those investors that were contacted on the same day by the same adviser, but did not answer the phone call. Treated is the estimated coefficient $\hat{\beta}$ from the following equation, which we estimate by OLS:

$$Change\ Outcome_i = \alpha + \beta \times Treated_i + \epsilon_i$$

Panel A reports results for the disposition effect, where *Change Outcome* is the difference between the proportion of gains realized (PGR) and the proportion of losses realized (PLR) for each investor before and after using the optimizer. Panel B reports the results for trend chasing. *Change Outcome* is the difference between the average number of days in which a stock purchased by the investor had positive daily returns among the 5 business days before the purchase, before and after adoption. Panel C and Panel D report the results for the rank effect. *Change Outcome* is the average difference between the number of best/worst performing stocks sold and the number of mid-performing stocks sold before and after the use of the optimizer. For each difference-in-differences coefficient we report the associated p-value and the number of observations in the regression.