The Impact of Robo-advising on Investment Planning

Vishaal Baulkaran
Associate Professor of Finance
Dhillon School of Business
University of Lethbridge
Tel: 403-329-2074
Email: vishaal.baulkaran@uleth.ca

Pawan Jain
Assistant Professor of Finance
John Chambers College of Business and Economics
West Virginia University
Email: pawan.jain@mail.wvu.edu

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Abstract

Using propriety data from a large Robo-advisory firm from India, we show that users of Robo-advisory services are relatively young, predominantly male, married, small investors, and professionals. We show that the majority of small retail investors utilized a systematic investment plan (SIP). Additionally, we document that there are differences in demographic characteristics, occupation and geographic location of investors, in utilizing SIP versus one-time lump sum investments. Furthermore, we find that the daily user account creation increases during the period of high market volatility. Finally, we show that SIP investors and those with diversified portfolios generate positive risk-adjusted returns.

JEL: D14, G11, G51, O33
Keywords: Robo-advisory, FinTech, Systematic Investment Plans, Lump Sum Investments

I. Introduction

It is well established that investors benefit from stock market participation. However, the potential benefits are predicated for well-diversified portfolios (see for e.g Campbell and Viceira 2002; Campbell, 2006; and D'Acunto, Prabhala and Rossi, 2019). Financial advisors, both human and robo, can aid investors in constructing a well-diversified portfolio to benefit from stock market participation. Foerster, Linnainmaa, Melzer, and Previtero (2017) argue that, unlike human financial advisors, robo-advisors are not prone to behavioral biases and cognitive limitations and hence, are programmed to objectively construct diversified portfolios.[1] Also, for many small retail investors, services by traditional financial advisors are prohibitively costly. Robo-advisory firms allow small retail investors to participate in the stock market at very low costs.[2] Furthermore, robo-advisors are transparent, provide information to clients in real-time, and have greater simplicity and efficiency in implementation strategies due to pre-built automated algorithms, relative to traditional human financial advisors.

Automated investment advice is relatively new but developing quickly. Hence, there is limited empirical evidence on this emerging financial technology. While there is an increased volume of research in this area, several questions remain unanswered such as: who is likely to utilize the robo-advisory services? Does it provide access to stock market investments for very small retail investors? Are investors more likely to have a low-cost diversified portfolio? Do Robo-advisory participants perform better or worse compared to the general stock market? Do these services motivate investors to save periodically and how does this type of systematic investment

[1] Robo-advising tools might be subject to the biases, conflicts and limitations of the humans and institutions that develop them (D'Acunto, Prabhala and Rossi, 2019).

[2] Robo-advisory is based on the principle of lower management fees through passive investment vehicles, 24/7 access to client's portfolio on mobile devices, easier onboarding processes, and algorithm enhanced decision making for less sophisticated investors who would otherwise not be qualified for a traditional human financial advisor (Clarke, 2020).

impact the risk-adjusted returns? In this paper, we utilize data from a large independent Indian Robo-advisory firm to address the above questions.[3]

We show that users of Robo-advisory services in our sample are relatively young (average age: 38.3 years), predominantly male, married, professionals who earn between 500k to 1M Rupees per year (approximately U.S $6.8k to $13.6k per year). The majority are small retail investors that invest using systematic investment plans (SIP). We show that the probability of funding an account with a Robo-advisory firm is higher for older investors, married individuals, those employed in the public sector and the investors who are closer to a financial center and are located in an urban area. Furthermore, we show that demographic characteristics, occupation and geographic location influence whether investors invest via a periodic investment plan or a one-time lump sum investment. Additionally, we find that user account creation increases during periods of high market volatility. Furthermore, we show that funded accounts with lump sum investment increases during high market volatility periods while SIP funded account creation decreases for the same high volatility periods. Finally, we find that individuals who invest via periodic investment plan and those with diversified portfolios generate positive risk-adjusted returns.

Our paper makes several significant contributions towards the growing literature on Fintech and, in particular, Robo-advising. While there has been limited evidence of the benefits of fintech in asset management, our paper is among the first to analyze the client data from a large independent Robo-advising firm. Our study differs from D'Acunto, Prabhala and Rossi (2019) as they analyze the impact of the introduction of a portfolio optimization software in an existing wealth advisory firm that serves small and large investors while we analyze the data from a Robo

[3] The selected Robo-advisory firm is very representative of the industry as it has clients all across India (see figure 1).

advisory firm that caters primarily to retail investors. Our dataset also contains richer demographic data such as age, gender, marital status, occupation and geographic locations. In addition to contributing to the literature on diffusion of technological innovation and identifying the profile of adopters of Robo advisory services, our paper is the first to evaluate the differences between the clients who invest a consistent amount systematically vs. the clients who invest larger lump sum amounts randomly. Our study contributes to the literature on savings and investments as well as the impact of Robo-advisors on wealth management in general. Furthermore, we are among the first to document that volatility leads to a greater interest in Robo-advising services. We also show that during periods of volatile market conditions, the investors are perhaps trying to time the market as is evident by an increase in one-time lump sum investments.[4] Finally, we contribute to the asset pricing literature by documenting positive risk-adjusted returns to systematic investments and diversified portfolios.

The remainder of the paper is organized as follows: in section 2 we review the literature, section 3 contains the data description and methodology, section 4 reports the results and section 5 concludes the paper.

II. Literature Review

Robo-Advisors use an algorithm based on modern portfolio theory to construct, monitor and rebalance low-cost portfolios in an efficient manner (Bjerknes and Vukovic, 2017). Their low-cost advantage is due to a reduction in fixed costs such as salaries to advisors and reduced the need for physical office space as well as utilizing low cost products such as ETFs to construct efficient and diversified portfolios (Uhl and Rohner, 2018 and Alsabah, Capone, Lacedelli and Stern, 2020).

[4] This is also evident in practice such as Robinhood, a small investor brokerage house that experienced unprecedented growth during the COVID pandemic (https://marker.medium.com/how-robinhood-convinced-millennials-to-trade-their-way-through-a-pandemic-1a1db97c7e08).

Furthermore, Robo-advisors provide transparent and systematic advice, mitigate the bias of data gathering and investors' recommendations process that is typical of human advising as well as potential behavioural biases among investors (Foerster et al. 2017 and Uhl and Rohner, 2018). Finally, Robo-advisors provide mostly passive market access with strategic asset allocations versus traditional investment advisors offering active market calls (Uhl and Rohner, 2018).

In addition, Robo-advisors have emerged as a significant disruptor to traditional human advisory services and as a result, have been adopted by larger investment management companies such as Vanguard and BlackRock (Alsabah et al., 2020). According to Statista, assets under management in the Robo-advisors segment are projected to reach U.S $682.7 billion in 2020 and $1.68 trillion by 2024. Furthermore, amid the Covid-19 related market upheaval, Robo advisors are gaining new, younger clients because automated accounts are generally cheaper due to the use of computer algorithms than human money managers. Robo-advisors are especially attractive to younger investors who have time to grow their savings before retirement. For example, Wealthfront's average customer age is 32 while Betterment's is 37 (Rockeman, 2020). In fact, Awuni (2019) argues that Robo-advisors are extending financial advice to everyone especially the younger demographic such as millennials and generation Z who seek control over their finances. Furthermore, Robo-advisors are influencing how many baby boomers and seniors purchase and consume wealth services, thereby challenging human-based business models that typically have higher fees.

According to a report by Deloitte, significantly lower fees (and in some cases zero fees) compared to traditional fees has broadened the market for advice to include the majority chunk of untapped wealth in the United States. Similarly, Britton et al. (2017) argue that Robo-advisors allow access of the market to mass consumers (i.e., assets < $200K) who seek affordable financial advice that appears to be tailored to their unique needs. In addition, Robo-advisors play into the common preferences of a new generation of wealth that is, more in control, digitally savvy and anywhere/anytime preference. Thus, the adoption of Robo-advisors results in a new class of investors that have not been served by the traditional wealth management industry (Jung, 2018).

In a FINRA (2016b) survey, 38 percent of individuals aged 18 to 34 in the U.S with investments outside of a pension plan have used a Robo-advisor compared to 4 percent of individuals aged 55+. On the other hand, a 2016 Gallup survey finds that more than 70 percent of U.S investors believe that human advisors are better than Robo-advisors to serve investors' best interests, make good investment recommendations, take each client financial picture into account, advise clients on risks, make clients feel confident about their investments and help clients to understand their investments. Hence, there is a debate on the effectiveness of Robo-advisory services as compared to human advisors in practice.

Although Robo-advisory is growing in popularity in academic literature, limited empirical evidence exists on the impact of Robo-advisory on wealth management, its types of clients and its impact on savings and retirement planning. One of the first studies to examine the impact of Robo-advising is D'Acunto, Prabhala and Rossi (2019). They show that adopters of a portfolio optimizer are similar to non-adopters in terms of demographics and prior interaction with human advisors but tend to be more active and have greater assets under management. They show that undiversified investors increase their stock holdings and hold a portfolio with less volatility and better returns while well-diversified investors hold fewer stocks, see some reduction in volatility and trade more after adoption. Finally, they show that adopters exhibit declines in behavioral biases including the disposition, trend-chasing and rank effect.

Loos, Previtero, Scheurle and Hackethal (2020), using data from a large German retail bank, find that after joining a Robo-advising service, clients increase financial risk-taking, hold more diversified portfolios with a larger fraction of index funds, exhibit lower home bias and trend-chasing and increase their (buy) turnover. Also, they find that investors also learn from the Robo-advisory tool, as evidenced by an improvement in portfolio efficiency in the non-Robo advised part of their portfolio.

Using the 2015 state-by-state National Financial Capability Study and Investor Survey, Lu and Chatterjee (2020) find that the need to free up time, higher risk tolerance, higher subjective financial knowledge and higher amounts of investable assets were positively associated with individual investors' adoption of Robo-advisors. Additionally, individuals under 65 who are more likely to possess higher amounts of investable assets, have higher risk tolerance and with greater perceived investment knowledge, were more likely to use Robo-advisors. They argue that their findings are contrary to the popular view in the financial services industry that Robo-advisors are viewed favorably as being able to lower the entry-level barriers to professional financial advice, which might be beneficial for investors of modest means who are trying to save for their retirement.

Start-up Robo-advisors have been increasing since 2014 and there are no signs that the trend will decline as their clients continue to adapt their products at a fast pace due to ease of access and low cost (Awuni, 2019). Furthermore, asset management for low net worth individuals is in a nascent stage of undergoing a complete revolution as these technologies continue to develop. In addition, traditional human advisors and large financial institutions have ignored a large segment of the retail investors’ population with assets less than 250k. It is possible that Robo-advisors are filling this gap. Hence, Robo-advisors may be ideal for smaller retail investors and individuals who are more comfortable with new technology.

While signing up for Robo-advising services is simpler, the Robo-advising firms collect a tremendous amount of data to not only meet the compliance requirements but also to provide customized portfolio solutions to meet individual client needs. After registering on a Robo-advisor's website, the next step of interaction is to fill an online questionnaire designed to extract the personal information needed to construct a suitable investment portfolio and to obtain compliance with the regulators (Jung, Dorner, Glaser and Morana, 2018). These questions include age, monthly income, savings objective, level of knowledge of financial instruments (Hakala, 2019). In addition, Ji (2018) argues that some Robo-advisor algorithms check the consistency of the provided answers and flag any inconsistencies prompting for a revision. Using the client's answers from the questionnaire, a risk-return is developed for the customer and finally, providing the actual recommendation for portfolio allocation which takes into consideration the client's risk preferences, investment goals, tax conditions, and investment horizon (Hakala, 2019). Ultimately, modern portfolio theory uses a mathematical framework to calculate portfolios for which the expected return is maximized for a given level of portfolio risk (Lam 2016).

III. Data and Methodology

This study uses proprietary data from a Robo advisory firm in India. The Indian advisory firm provided a snapshot of all user accounts. The dataset contains information on investors' asset allocations, redemption, frequency of savings (continuous vs lump sum or both) along with rich demographic information such as age, marital status, employment type, location, etc. We started with over 1.5 million accounts created by investors. We filtered our data to ensure that we had complete demographic information for all investors in our sample. We cleaned our data by deleting less than 0.5% of observations with disclosed ages of less than 18 or greater than 90. This screening procedure resulted in 279,434 user accounts with complete demographic information in the sample of which, 185,950 have invested via the Robo-advisory firms while 93,484 have not invested an amount. Furthermore, we obtained state-level data such as population, education level and economic data from the Reserve Bank of India which are used as control variables in our empirical models below.[5]

In figure 1, we show the number of Robo-advisory users by state. Even though few states account for over 10% of the users, the sample is fairly distributed across the country. In table 1 panel A, we summarized the data by users of the Robo-advisory services and those individuals who created an account but have not invested with the Robo-advisory firm (non-users). In this table, we tabulated the data for the top-ten states. The top four states (Maharashtra, Uttar Pradesh, Tamil Nadu and West Bengal) account for 49% of the user sample compared to 42.4% of the non-user sample by the top 4 states (Maharashtra, Uttar Pradesh, Karnataka and Tamil Nadu). The top ten states account for 77.3% of the sample of the users while the top ten states account for 72.9% of the non-user sample.[6] In panel B, we report income grouping for user and non-user groups. In terms of the user group, 4.3% of the sample earns below Rs. 100,000, 17% between Rs. 100k and Rs. 500k, while the majority of the sample (76.6%) earns between Rs. 500k - Rs. 1M. Similar statistics are reported for the non-user group.

In panel C, we report the occupation for the user and non-user groups. Individuals who report private sector as their occupation account for 83.7% of the user sub-sample. The next largest group is public sector employees (8.8%), followed by the business owners (3.8%). We observed a similar trend for the non-user group. For example, the private sector accounts for 79% of the non-

[5] For further details on how the variables are created please see Handbook of Statistics on Indian Economy (2020).
[6] The user group subsample are accounts that are funded while the non-user group are accounts with complete demographic information but have not been funded by the investor.

user group, followed by individuals employed in the public sector (7.6%) and individuals who own businesses (4.8%).

Overall, it appears that users of funded accounts are similar to those who do not fund their accounts based on location, income and occupation groupings. However, we conduct more rigorous test using the following Probit model:

$$USER_i = \propto + \sum_i \beta_i * CLIENT_i + \sum_i \gamma_i * STATE_i + YEAR_i + \varepsilon_i,$$

where *USER* is a dummy variable that takes a value of 1 for all the individuals who fund their accounts and zero for the individuals who provided the demographic information but did not fund the account. *CLIENT* includes all the client specific control variables such as age, gender, number of days since the account was first created on the platform, marital status, occupation, income, and location. *STATE* includes all the state specific controls for the state in India where the individual submitting the information in the Robo-advisory platform is located. These include the urban population, GDP growth rate, inflation, importance of banking and insurance industry, passive and active investment, personal loans, and bank deposits. We also include the year fixed effects, *YEAR*, to control for the advancement of technology and other year specific variations that are not accounted for by our selected control variables.

The advising platform provides clients with the option to systematically fund the account at a fixed interval. To test whether there is a difference between clients who choose to save systematically vs others, we use a similar regression model as the one we use for USER above. We change the dependent variable to *SIP* which takes the value of 1 if the client is identified as an investor who saves systematically, zero otherwise. Similarly, to test if there are differences between clients who fund their accounts randomly, we create a dummy variable, *ONETIME,* that takes a value of 1 for the client who funds the account randomly, zero otherwise. Note that a client can do both, systematic investments and random investments.

IV. Results

4. 1. Descriptive Statistics

In table 2, we report descriptive statistics for users (panel A) and non-users (panel B). In panel A, we show that the average age for Robo-advisory users is 38.3 years, 75% are married and 79% males. Unlike D'Acunto, Prabhala, and Rossi (2019), individuals utilizing Robo-advisory services in our sample are younger as well as more likely to be male. Similarly, the amount invested, the mean is Rs. 68,081 (median = Rs.9,000), which is much smaller than the average in the D'Acunto et al. (2019) study. In fact, we argue that Robo-advisor is beneficial for investors of modest means who are trying to save for their retirement as indicated by the average amount invested. Unlike traditional advisory firms, Robo-advisors do not have any minimum requirements for funding the account. This enables younger investors to build wealth earlier which is critical when longer time horizons and interest compounding are the greatest advantages to increasing retirement savings and investments. To date, the evidence shows that younger people in their 20s and 30s are more likely to use robo-advisors than older people. For example, the average age of Betterment's clients is 36, a number that will rise as young robo users' age (Wang and Padley,2017). Additionally, younger people's smaller asset base makes them less suitable clients for traditional financial advisors (Stein, 2016). The average age in our sample is similar to the average age of Betterment's clients.

In terms of asset class, the mean equity investment is Rs. 50,736 (median = Rs. 9,000 and mode=1,000), while mean investments in debt instrument is Rs. 144,578 (median= Rs. 10,000 and mode=1,000) and liquid investments (such as t-bills) have a mean of Rs. 364,371 (median= Rs. 3,000 and mode= Rs. 1,000). Our data allows us to examine total redemption as well as equity, debt and liquid investments. In terms of total redemption, the mean is Rs. 70,108 (median= Rs. 6,000 and mode= Rs. 1,000). The mean equity redemption is Rs. 37,769 (median = Rs. 6,000) while debt is Rs. 145,320 (median= Rs. 10,000) and liquid investment is Rs. 465,966 (median= Rs. 2,400), respectively. Finally, our dataset includes variables for schematic investments plan (SIP) per month as well as one-time lump sum investments. The average SIP is very small (Rs. 1,252) whereas the average one-time investment is Rs. 32,983. However, the median SIP and one-time investments is Rs. 1,000. This indicates the presence of rounding bias among the retail investor as documented in the behavioral finance literature (see Li, 2007).

In panel B, we report the non-user sample. Of the individuals who created accounts but did not invests, the average age is 33.56 years. This is 4.8 years younger than the user group, while married individuals account for 61% of the non-user sample. This is 14% less than the user group. Furthermore, 88% of the non-user group are males. This represents 9% more compared to the user group.

4.2. Regression Results

4.2.1 User Profile

In table 3, we report the results of our Probit model. Our dependent variable *user* is equal to 1 if the account is funded and 0 otherwise. In model 1, we regress several demographic and location variables on the user indicator variable. We show that the probability of funding the account increases with age, married individuals and income levels. Unlike David and Sade (2020) who show in their survey results that males are more willing to adopt and pay for service by algorithm, we find that males are less likely to fund an account once it is created. Also, the longer the account has been created, the lower the likelihood of being funded. In terms of occupations, all occupations increase the probability of funding an account, except retired individuals. As for geographic location, the accounts are being funded by users from across India and hence our sample is very representative of the broader population. In models 2 and 3 (year fixed effects), we control for state-level macroeconomic variables such as Bank-Insurance Value-added, lag GDP growth, invested capital, personal loans, urban population and bank deposits and include the year fixed effects. The results are similar to model 1, except geographic location variables are no longer significant.

4.2.2 Systematic Investment Plan (SIP) Vs. One-time Lump Sum Investment

Next, we examine the impact of a systematic investment plan (SIP) versus a one-time lump sum investment amount.[7] In table 4, we report the Probit model for SIP. In model 1, we show that older individuals and older created accounts are less likely to utilize SIP to invest via Robo-advisors. However, male and married individuals are more likely to use SIP. Similarly, individuals employed in the private and public sector as well as business owners are more likely to invest via SIP while students are less likely. The results seem intuitive. For example, government or company-sponsored retirement plans in India in inadequate or do not provide sufficient income in retirement. Hence, our findings suggest that individuals employed in the public or private sector save and invest via Robo-advisors. A similar argument applies to business owners with no established pension plan. In terms of students, they are less likely to utilize SIP. Again, the results are intuitive since students do not have regular monthly income, it is not feasible for them to invest

[7] Dataset provides us with an identifier for the clients who chose SIP.

via a periodic investment plan. In models 2 and 3, we control for state-level macroeconomic variables and include year-fixed effects and the results are similar to model 1 except income is positive and significant.

O'Neil (2007) argues that automatic investment plans enable the process of dollar-cost averaging. Although, dollar-cost averaging does not guarantee a profit or protect against losses in a down market, it does bring a discipline to the investing process that many people are unable to achieve otherwise on their own (Pursuing a Systematic Approach, 2005). Furthermore, dollar-costing takes the emotion out of investing due to deposits made at regular intervals (O'Neil, 2007). Furthermore, Dubil (2005) shows that the major benefit of dollar-cost averaging is risk reduction, especially for long-term investors. Our results are consistent with the above arguments. Given that it is unlikely that a proportion of individuals in our sample have a defined benefit pension plan, the majority are utilizing Robo-advisors in order to invest for retirement and hence, are likely to be long-term investors. In addition, our findings are consistent with Brauer, Hackethal, and Scheurle (2017). They show that robo-advice has a significantly positive effect on automatic recurring investment (fund savings plans) choice compared to self-directed savings plans in three regards: (1) increased diversification, (2) increased share of passive investment in ETFs by 23.5 percentage-points, and (3) increasing choice of less costly ETFs leading to a reduction in the average total expense ratio of savings plans.

In table 5, we report the factors influencing one-time lump sum investments with Robo-advisors. The results for one-time investments appear contrary to the SIP results. For example, age is positively related to one-time investments. This suggests that older individuals make lump sum investments due to larger disposal assets/income. This is consistent with the life theory of consumption and savings. Males and married individuals and longer unfunded accounts are less likely to invest via lump sum. In terms of occupations, the public sector, private sector, professionals, business owners and retired individuals are more likely to invest via lump sum amounts. The results in models 2 and 3 are similar to model 1 after accounting for state-level macroeconomic variables.

4.2.3. Market Volatility

Next, we examine whether market volatility increases the use of Robo-advisory services and whether volatility affects SIP and one-time investments differently. Market volatility can drive young and new investors to utilize a Robo-advisor in order take advantage of opportunities in the market created by volatility. For example, Robinhood saw account creation and funding at record levels during periods of increased market volatility as a result of the economic impact of the Covid-19 Pandemic (Walker, 2020). Furthermore, it is likely that these accounts are funded with lump sum investments rather than systematic recurring investments (SIP). That is, the volatility attracts investors who are looking for opportunistic trading and investments rather than those who are slowly accumulating wealth for retirement.

In table 6, we report the results of our Tobit model for the number of user accounts created daily. In column I, we examine the effect of market volatility on user account creation. Our results show that volatility has a positive and significant impact on user creation. This is consistent with anecdotal evidence in media that investors tend to utilize Robo-advisory service during volatile periods. A potential alternate explanation for this phenomenon could be that the market momentum rather than opportunistic trading is driving user account creations. In column II, we examine this including market returns in our Tobit model. While in column III we include both market returns and volatility. We show that investors flocking to Robo-advisory firms during periods of high volatility and the results are not driven by market momentum.

In table 7, we further examine which type of investors are more likely to create and use Robo-advisory services. We expect those investors with lump sum investments are more likely to utilize Robo-advisory services for opportunistic trading during periods of high market volatility compared to investors saving for retirement via SIP. In column I, we report the results of investors who utilized SIP. As expected, market volatility is negative and statistically significant. On the other hand, as expected, market volatility has a positive and statistically significant impact on investors utilizing lump sum investments via Robo-advisors. This is consistent with the conjecture that these investors are seeking to take advantage of opportunism created by market volatility.

4.2.4 Holding Period Returns

Next, we turn our attention to the holding period returns generated by the Robo-advisory users. We estimate the following Fama-French 4-factor model to test if the clients generate positive risk-adjusted returns. We also test if the returns are higher for clients with *SIP* and the ones that hold a diversified portfolio with investments in stocks, bonds, and short-term liquid assets.

$$HPR_i - RF_i = \propto + \beta_1 (MKTRET - RF)_t + \beta_2 SMB_t + \beta_2 HML_t + \beta_2 MOM_t + \varepsilon_i$$

where,

$$HPR_i = \frac{AUM_i + Redemption_i}{InvestedAmt_i} - 1$$

HPR is the holding period return for client *i* and is calculated as a ratio of the sum of the asset under management (*AUM*) as of October 19, 2020 and redemption amount (*Redemption*) to the amount invested (*InvestedAmt*) minus 1. *RF* is the risk-free rate, *MKTRET* is the market return, *SML*, *HML*, and *MOM* are the size, growth, and momentum risk factors, respectively. We obtained the data on the risk factors for the emerging markets from Kenneth French's website and aggregate the factor returns and risk-free rate to the same time period as the holding period returns. All the variables are defined in the Appendix.

We report our findings in table 8. In model 1, after controlling for the 4-factors, we find a negative and significant alpha suggesting that, in general, the robo advising clients are underperforming the broader market indices. However, in model 2 we show that individuals who invest using SIPs generate positive returns as compared to other clients. Similar to D'Acunto et al. (2019), in model 3, we find that individuals who diversified their portfolio with equity ETFs, Bond ETFs and T-bills (Liquid ETFs) generate significantly higher returns than the ones who hold an undiversified portfolio after controlling for Fama-French 4-factors.

A study by T. Rowe Price (Pursuing a Systematic Approach, 2005) shows that investors who make a lump sum at the start of each year typically outperform those who invest monthly. However, SIPs experienced less volatility and better results during poor performing bear markets. Our results differ in that we show SIP investments generate positive returns. This is likely due to the dollar-cost averaging effects as well as compounding effects of SIP. This is consistent with findings of Brauer, Hackethal and Scheurle (2017) and the theoretical predictions in Capponi, Olafsson, and Zariphopoulou (2021).

V. Discussion and Conclusion

Using a unique dataset for an Indian Robo-advisory firm, our aim is to shed light on several important questions pertaining to the popularity of Robo-advisors. Questions such as who is likely to utilize the service? Does it provide access to stock market investments for very small retail investors? Our data contains extensive demographic, occupational and geographic information which we utilized to address the above questions. We document several characteristics that influence the utilization of Robo-advisory services such as age, gender, marital status and occupation. Furthermore, we show that Robo-advisory firms allow small retail investors to access the stock at very low costs via SIPs as well as one-time lump sum investments. In fact, a majority of the Robo-advisory clients earn less than U.S $16K per year. This is consistent with the argument by Britton et al. (2017) that Robo-advisors allow access of the market to mass consumers who seek affordable financial advice that appears to be tailored to their unique needs. Also, we provide empirical evidence that user account creation increases during periods of high market volatility. In fact, investors utilizing lump sum investments increase significantly during high volatility periods while for SIP investors, user account creation decreases significantly during periods of high volatility. We argue that lump sum investors seek to take advantage of opportunities created by market volatility while SIP investors save and invest small amounts for retirement.

Furthermore, we show that investing via SIP and holding diversified portfolios produce positive market-adjusted returns. This is consistent with the findings of Loos et al. (2020) and D'Acunto (2019). In addition, Madrian and Shea (2001) find that switching 401 (k) to automatic and immediate enrollment dramatically changed the savings behaviour of employees in their study.[8] They argue that automatic investment reduces financial inertia. Although investors in our sample are less likely to suffer from financial inertia related to saving and investing since these are self-directed investment accounts created using a Robo-advisory firm, we show that SIP investment accounts produce significant market-adjusted returns benefiting from dollar-cost averaging and compounding.[9]

[8] They analyze the 401(k) savings behavior of employees in a large U. S. corporation before and after an interesting change in the company 401(k) plan.
[9] Financial inertia results from a number of psychological and behavioral biases such as status quo, anchoring around default option, etc.

While there has been significant attention on employer sponsored savings and retirement plans (see for e.g. Thaler and Benartzi, 2004, Madrian and Shea, 2001 Choi at al., 2002 and 2004), little is known about self-directed individual investors systematic savings plans outside employer sponsored plans. Our study on Robo-advisors and their role in enabling self-directed SIP in the absence of employer sponsored plans make a unique contribution to the literature on savings and investments as well as the impact of Robo-advisors on wealth management in general.

One possible limitation is that our study uses the data from India, where the regulatory and institutional framework is different from the U.S and other developed economies. However, the Indian stock exchanges are leading markets globally. According to the statistics published by the World Federation of Exchanges in 2019, National Stock Exchange of India is the third largest exchange globally in terms of number of trades in common stocks and is ranked first in terms of number of options contracts traded across the world. The mutual fund industry is one of the fastest growing segments of the financial sector in India. In the last decade, the asset under management for the mutual fund industry has grown at a rate of 13.7 per cent per year, translating into more than 350 percent increase in a span of 10 years (SEBI annual report, 2021). India has also been leading the charts with 87% adoption rate for financial technologies as compared to 46% for the United States (Ernest Young global Fintech adoption index, 2019).[10] Of particular interest is the increasing usage of artificial intelligence and machine learning in investor and consumer facing products (e.g. robo advising) (SEBI annual report, 2021). Technology-driven financial service firms are going beyond simply distributing mutual funds to offering digitized, long-term financial planning solutions.

[10] https://www.ey.com/en_us/ey-global-fintech-adoption-index

Robo advisors use computer algorithms to gather and analyze the financial position, goals, aspirations, and risk appetite of users to provide personalized financial planning advice.[11] Additionally, given that robo-advisory firms target investors that are typically ignored by mainstream financial institutions and human financial advisors, the characteristics of investors are generally the same regardless of whether they located in developing markets (India) or developed markets (U.S). From this point of view, we believe our results are generalizable.

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Figure 1: Robo-Advisory Users

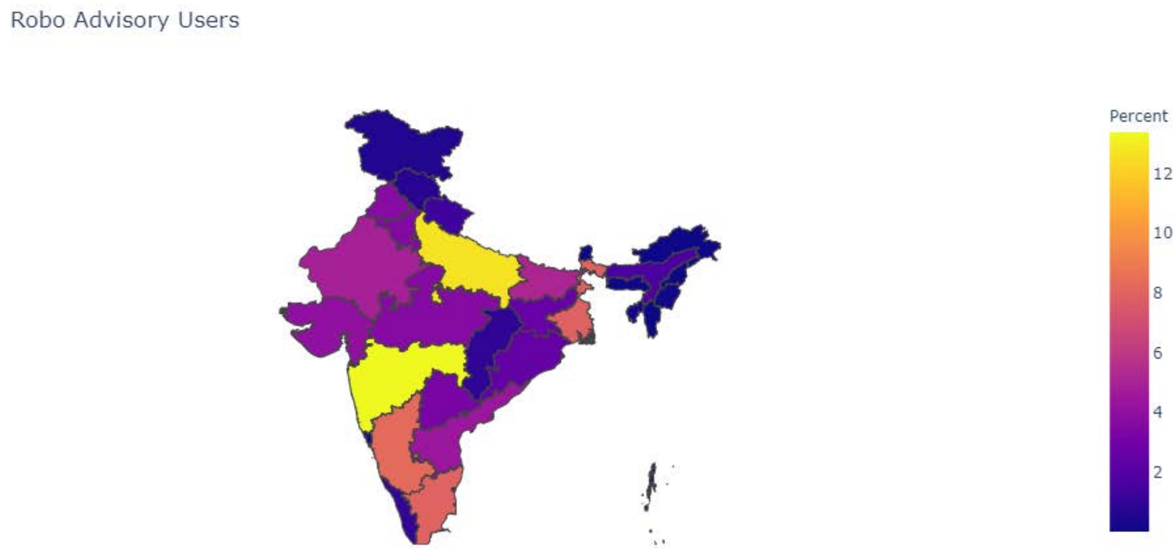

Table 1: Top-ten states

Panel A: User and non-user by top-ten states.

State	# of user A/C	% of users	Non-Users	# of non-user A/C	% of non-users
Maharashtra	27,995	14.99	Maharashtra	16,183	13.39
Uttar Pradesh	21,452	11.49	Uttar Pradesh	15,356	12.71
Tamil Nadu	21,144	11.32	Karnataka	10,031	8.30
West Bengal	20,871	11.18	Tamil Nadu	9,679	8.01
Karnataka	14,178	7.59	West Bengal	9,572	7.92
Punjab	9,365	5.02	Bihar	6,274	5.19
Bihar	7,984	4.28	Rajasthan	5,954	4.93
Andhra Pradesh	7,757	4.15	Andhra Pradesh	5,392	4.46
Rajasthan	7,286	3.90	Gujarat	4,956	4.10
Madhya Pradesh	6,230	3.34	Delhi	4,654	3.85

Panel B: Income grouping for user and non-user group.

Income (Users)	# of user A/C	% of users	Income (Non-Users)	# of non-user A/C	% of non-users
Below 100K	8,090	4.338	Below 100K	9,883	7.891
100K-500K	31,713	17.007	100K-500K	26,495	21.155
500K-1 M	142,865	76.615	500K-1 M	85,155	67.993
1M-2.5M	3,344	1.793	1M-2.5M	2,980	2.379
2.5M-10M	432	0.232	2.5M-10M	622	0.497
Above 10M	27	0.014	Above 10M	105	0.084

Panel C: Occupation by user and non-user group.

Occupation (Users)	# of user A/C	% of users	Occupation (Non-Users)	# of non-user A/C	% of non-users
Private sector	155,987	83.650	Private sector	101,515	79.066
Public sector	16,449	8.821	Public sector	9,761	7.602
Professional	1,815	0.973	Professional	2,904	2.262
Housewife	1,457	0.781	Housewife	926	0.721
Business	7,106	3.811	Business	6,174	4.809
Retired	877	0.470	Retired	532	0.414
Student	1,540	0.826	Student	3,345	2.605
Others	1,245	0.668	Others	3,188	2.483

Table 2: Descriptive Statistics

Panel A: Robo-Advisory Users

Variable	N	Mean	Median	Mode	SD	Min	Max
Age	187,030	38.2960	35	30	11.8717	18	90
Income	186,471	2.7662	3	3	0.5634	1	6
Married	186,338	0.7503	1	1	0.4328	0	1
Male	186,185	0.7883	1	1	0.4085	0	1
Female	186,185	0.2116	0	0	0.4085	0	1
Invested Amount	187,549	68,081.5	9,000	1,000	3,586,965	0	1,499,952,502
AUM	187,549	38,376.6	3,347	0	566,804	-2,818,699	101,125,150
Equity invested amt.	183,314	50,736.3	9,000	1,000	590,621	100	109,881,639
Debt invested amt.	9,421	144,578.7	10,000	1,000	2,073,901	100	99,995,000
Liquid invested amt.	5,769	364,371.9	3,000	1,000	19,127,841	100	1,449,952,502
Redemption amt.	81,906	70,108.7	6,000	1,000	5,319,555	0	1,499,952,502
Equity redemption amt.	78,276	37,769.1	6,000	1,000	546,150	0	102,862,571
Debt redemption amt.	5,757	145,320.2	10,,000	1,000	1,802,790	0	70,332,586
Liquid redemption amt.	4,183	465,966.8	2400	1,000	22,443,798	0	1,449,952,502
Avg. SIP	164,828	1,251.6	1,000	1,000	3,460	100	500,000
Avg. Onetime	62,387	32,983.3	1,000	1,000	1,038,582	100	249,992,084

Panel B: Robo-Advisory Non-Users

Variable	N	Mean	Median	Mode	SD	Min	Max	Mean Diff: Non-Users-Users
Age	192,790	33.5601	31	30	9.8852	18	90	-4.7359***
Income	125,240	2.6669	3	3	0.6837	1	6	-0.0993***
Married	141,087	0.6148	1	1	0.4866	0	1	-0.1355***
Male	135,002	0.8809	1	1	0.3240	0	1	0.0926***
Female	135,002	0.1170	0	0	0.3214	0	1	-0.0946***

Table 3: Probit model: User vs non-users

The dependent variable user equal to 1 if investors fund the account and zero otherwise. Explanatory variables are defined in Appendix 1 Table 2A. ***,**,* represents 1%, 5% and 10% significant levels. The standard errors are reported in parentheses.

	Model 1	Model 2	Model 3
Intercept	-0.6370***	0.0474	-0.0051
	(0.1268)	(0.1751)	(0.3367)
Age	0.0204***	0.0200***	0.0193***
	(0.0003)	(0.0003)	(0.0003)
Male	-0.2806***	-0.2742***	-0.2637***
	(0.0069)	(0.0070)	(0.0071)
#days	-0.0007***	-0.0007***	-0.0001*
	(0.0000)	(0.0000)	(0.0000)
Income	0.0180***	0.0275***	0.0368***
	(0.0045)	(0.0046)	(0.0047)
Married	0.0712***	0.0733***	0.0710***
	(0.0063)	(0.0064)	(0.0065)
Private sector	0.2526***	0.2465***	0.1712***
	(0.0255)	(0.0260)	(0.0261)
Public sector	0.5406***	0.5334***	0.4391***
	(0.0267)	(0.0273)	(0.0274)
Professional	0.0585*	0.0705**	0.0094
	(0.0330)	(0.0336)	(0.0338)
Housewife	0.1643***	0.1672***	0.1669***
	(0.0382)	(0.0389)	(0.0390)
Business owner	0.2653***	0.2488***	0.1659***
	(0.0278)	(0.0284)	(0.0285)
Retired	0.0113	0.0096	-0.0386
	(0.0479)	(0.0489)	(0.0492)
Student	0.0862***	0.0980***	0.0542
	(0.0326)	(0.0333)	(0.0334)
North India	0.5444***	0.0266	0.2662
	(0.1232)	(0.1715)	(0.1803)
South India	0.7157***	0.0984	0.3855**
	(0.1232)	(0.1721)	(0.1809)
East India	0.6053***	0.0802	0.3345*
	(0.1233)	(0.1715)	(0.1803)
West India	0.6586***	-0.0783	0.2901
	(0.1233)	(0.1735)	(0.1823)
Central India	0.5139***	-0.0584	0.2203
	(0.1237)	(0.1718)	(0.1806)
North East India	0.4278***	-0.0042	0.1190
	(0.1244)	(0.1721)	(0.1809)
Lag CPI		-0.0449***	0.0534***
		(0.0025)	(0.0030)
Bank_Ins. Valueadd x10^4		0.0007***	0.0007***
		(0.0000)	(0.0000)
Lag GDP Growth		-0.0812	0.8894***
		(0.1138)	(0.1190)
Invested Capital x10^5		-0.0003***	-0.0003***
		(0.0000)	(0.0000)
Personal Loan x10^4		-0.0022	-0.0053***
		(0.0018)	(0.0000)
Urban Popn.		0.0874***	0.0748***
		(0.0044)	(0.0044)
Bank Deposit x10^4		-0.0058***	-0.0057***
		(0.0004)	(0.0004)
Year F.E.			YES
Pseudo R^2	0.067	0.071	0.087
No. of Obs.	279,434	270,735	270,735

Table 4: Probit model: Systematic Investment Plan (SIP)

The dependent variable equal to 1 if investors invest via a SIP and zero otherwise. Explanatory variables are defined in Appendix 1 Table 2A. ***,**,* represents 1%, 5% and 10% significant levels. The standard errors are reported in parentheses.

	Model 1	Model 2	Model 3
Intercept	1.6611***	2.4366***	0.6017
	(0.2392)	(0.2897)	(0.3690)
Age	-0.0172***	-0.0174***	-0.0176***
	(0.0004)	(0.0004)	(0.0004)
Male	0.1349***	0.1340***	0.1365***
	(0.0095)	(0.0098)	(0.0099)
#days	-0.0008***	-0.0008***	0.0000
	(0.0000)	(0.0000)	(0.0000)
Income	0.0115	0.0199***	0.0276***
	(0.0072)	(0.0074)	(0.0077)
Married	0.2205***	0.2079***	0.2000***
	(0.0105)	(0.0108)	(0.0109)
Private sector	0.2196***	0.2182***	0.1584***
	(0.0393)	(0.0404)	(0.0404)
Public sector	0.4323***	0.4070***	0.3245***
	(0.0416)	(0.0427)	(0.0428)
Professional	-0.0404	-0.0250	-0.0846
	(0.0510)	(0.0523)	(0.0526)
Housewife	-0.0730	-0.0439	-0.0542
	(0.0524)	(0.0537)	(0.0538)
Business owner	0.2738***	0.2651***	0.1925***
	(0.0431)	(0.0442)	(0.0444)
Retired	-0.0472	-0.0533	-0.1220**
	(0.0590)	(0.0605)	(0.0607)
Student	-0.6056***	-0.6329***	-0.6639***
	(0.0515)	(0.0528)	(0.0530)
North India	0.2785	-0.1050	0.2921
	(0.2349)	(0.2842)	(0.2974)
South India	-0.0232	-0.4965*	-0.0455
	(0.2348)	(0.2850)	(0.2981)
East India	0.3197	-0.0514	0.3491
	(0.2350)	(0.2844)	(0.2976)
West India	0.1632	-0.2257	0.2848
	(0.2349)	(0.2872)	(0.3004)
Central India	0.1771	-0.2803	0.1661
	(0.2356)	(0.2848)	(0.2980)
North East India	0.3890	0.1635	0.4436
	(0.2374)	(0.2859)	(0.2991)
Lag CPI		-0.1011***	0.0081
		(0.0041)	(0.0050)
Bank_Ins. Valueadd x10^4		0.0006***	0.0006***
		(0.0000)	(0.0000)
Lag GDP Growth		0.0163	0.8649***
		(0.1875)	(0.1945)
Invested Capital x10^5		-0.0006***	-0.0005***
		(0.0000)	(0.0000)
Personal Loan x10^4		-0.0008	-0.0030
		(0.0029)	(0.0029)
Urban Popn.		0.1360***	0.1160***
		(0.0068)	(0.0069)
Bank Deposit x10^4		-0.0067***	-0.0060***
		(0.0006)	(0.0006)
Year F.E.			YES
Pseudo r2	0.091	0.100	0.115
No. of Obs.	185,950	180,349	180,349

Table 5: Probit model: One-time investments

The dependent variable equal to 1 if investors invest via a one-time lump sum investment and zero otherwise. Explanatory variables are defined in Appendix 1 Table 2A. ***,**,* represents 1%, 5% and 10% significant levels. The standard errors are reported in parentheses.

	Model 1	**Model 2**	**Model 3**
Intercept	-0.8475***	-1.1070***	-0.3994
	(0.2335)	(0.2909)	(0.3479)
Age	0.0041***	0.0039***	0.0040***
	(0.0003)	(0.0003)	(0.0003)
Male	-0.0657***	-0.0649***	-0.0686***
	(0.0076)	(0.0077)	(0.0078)
#days	-0.0006***	-0.0006***	-0.0006***
	(0.0000)	(0.0000)	(0.0000)
Income	0.0383***	0.0352***	0.0226***
	(0.0060)	(0.0061)	(0.0062)
Married	-0.0560***	-0.0495***	-0.0549***
	(0.0081)	(0.0083)	(0.0083)
Private sector	0.1005**	0.1023**	0.0075
	(0.0423)	(0.0432)	(0.0432)
Public sector	0.5308***	0.5462***	0.4527***
	(0.0431)	(0.0441)	(0.0442)
Professional	0.4473***	0.4380***	0.3408***
	(0.0519)	(0.0530)	(0.0531)
Housewife	0.0791	0.0839	0.0390
	(0.0564)	(0.0574)	(0.0574)
Business owner	0.1043**	0.1144**	0.0287
	(0.0449)	(0.0458)	(0.0460)
Retired	0.5041***	0.5085***	0.4444***
	(0.0607)	(0.0618)	(0.0620)
Student	0.0029	0.0039	-0.0334
	(0.0562)	(0.0573)	(0.0576)
North India	0.4263*	0.5049*	0.7208**
	(0.2288)	(0.2858)	(0.2835)
South India	0.3412	0.7128**	0.9363***
	(0.2288)	(0.2864)	(0.2840)
East India	0.6807***	0.7740***	0.9808***
	(0.2289)	(0.2859)	(0.2835)
West India	0.2631	0.4555	0.7335**
	(0.2289)	(0.2879)	(0.2856)
Central India	0.4627**	0.6829**	0.8994***
	(0.2292)	(0.2861)	(0.2838)
North East India	0.8856***	1.1140***	1.2494***
	(0.2298)	(0.2864)	(0.2839)
Lag CPI		0.0046	0.0371***
		(0.0032)	(0.0037)
Bank_Ins. Valueadd x10^4		-0.0005***	-0.0004***
		(0.0000)	(0.0000)
Lag GDP Growth		-0.1323	1.2642***
		(0.1599)	(0.1667)
Invested Capital x10^5		-0.0000	-0.0000
		(0.0001)	(0.0001)
Personal Loan x10^4		-0.0202***	-0.0216***
		(0.0023)	(0.0023)
Urban Popn.		0.0016	0.0031
		(0.0055)	(0.0056)
Bank Deposit x10^4		0.0078***	0.0067***
		(0.0005)	(0.0005)
Year F.E.			YES
Pseudo r^2	0.041	0.044	0.05
No. of Obs.	185,950	180,349	180,349

Table 6: Tobit Model for account creation and market volatility

The dependent variable equal to number of user accounts created daily. Volatility is the rolling prior 90-day standard deviation of the market returns. Market returns is the daily returns on the Nifty 50 index. All other explanatory variables are defined in Appendix 1 Table 2A. ***,**,* represents 1%, 5% and 10% significant levels. Standard errors are reported in parentheses.

	I	**II**	**III**
Intercept	-1260.03	-913.86	-1243.05
	(2555.73)	(2574.98)	(2572.71)
Volatility	**530.30****		**537.12****
	(225.64)		**(226.93)**
Daily market returns		21.66	10.46
		(82.25)	(82.19)
North	879.19	752.76	839.07
	(2250.62)	(2265.35)	(2260.34)
South	-276.30	-322.02	-310.62
	(2246.27)	(2261.84)	(2256.55)
East	547.68	412.86	527.04
	(2267.51)	(2282.26)	(2277.43)
West	-507.51	-599.76	-528.37
	(2267.89)	(2282.77)	(2277.62)
Central	432.30	339.93	415.24
	(2413.22)	(2429.26)	(2423.79)
North East	-979.82	-965.85	-896.93
	(2418.78)	(2437.69)	(2432.16)
Lag_CPI	10.47	-10.78	4.71
	(131.53)	(134.49)	(134.34)
LagGDP_Growth	9481.93*	9345.15*	9797.08**
	(4918.08)	(4967.47)	(4959.52)
Year F.E.	YES	YES	YES
Pseudo r^2	0.057	0.056	0.057
N	1,202	1,193	1,193

Table 7: Probit model for market volatility, SIP and One-time investment

The dependent variable in column I is equal to 1 if investors invest via a SIP investment and zero otherwise. The dependent variable in column II is equal to 1 if investors invest via a one-time lump sum investment and zero otherwise. Volatility is the rolling prior 90-day standard deviation of the market returns. All other explanatory variables are defined in Appendix 1 Table 2A. ***,**,* represents 1%, 5% and 10% significant levels. Standard errors are reported in parentheses.

	I	**II**
	SIP	**One-time**
Intercept	0.9900**	-0.9811**
	(0.4118)	(0.4095)
Volatility	**-0.8154*** **	**0.5051*** **
	(0.0472)	**(0.0382)**
Age	-0.0187***	0.0051***
	(0.0004)	(0.0003)
Male	0.1505***	-0.0843***
	(0.0108)	(0.0085)
#days	-0.0002***	-0.0003***
	(0.0001)	(0.0000)
Income	0.0271***	0.0141**
	(0.0087)	(0.0070)
Married	0.1925***	-0.0607***
	(0.0122)	(0.0091)
Private sector	0.1409***	0.0727
	(0.0458)	(0.0505)
Public sector	0.3401***	0.5347***
	(0.0488)	(0.0516)
Professional	-0.1205**	0.4508***
	(0.0597)	(0.0614)
Housewife	-0.0545	0.1143*
	(0.0609)	(0.0662)
Business owner	0.1827***	0.1286**
	(0.0501)	(0.0532)
Retired	-0.1322*	0.4919***
	(0.0677)	(0.0704)
Student	-0.7016***	0.0802
	(0.0607)	(0.0667)
North India	0.3544	0.7970**
	(0.3042)	(0.3112)
South India	0.0290	0.9845***
	(0.3051)	(0.3118)
East India	0.3957	1.0700***
	(0.3044)	(0.3112)
West India	0.3343	0.7607**
	(0.3079)	(0.3136)
Central India	0.2243	0.9772***
	(0.3048)	(0.3115)
North East India	0.5359*	1.3515***
	(0.3063)	(0.3117)
State Level Control Variables	YES	YES
Year Fixed Effects	YES	YES
Pseudo r^2	0.119	0.053
N	151,823	151,823

Table 8: Holding Period Returns

Holding period returns is defined at (AUM +Redemption)/Amount invested -1. Explanatory variables are defined in Appendix 1 Table 2A. ***,**,* represents 1%, 5% and 10% significant levels. The standard errors are clustered by client and year and are reported in parentheses.

	Model 1	**Model 2**	**Model 3**
Alpha	-0.0031***	-0.0221***	-0.0125***
	(0.0008)	(0.0010)	(0.0009)
SIP		**0.0286*** **	
		(0.0008)	
Diversification			**0.0094*** **
			(0.0005)
mkt_rf	3.3807***	3.0942***	2.9024***
	(0.3043)	(0.3035)	(0.3054)
SMB	-4.4249***	-4.9079***	-4.7667***
	(1.1825)	(1.1572)	(1.1804)
HML	1.5365*	6.6543***	0.6126
	(0.8315)	(0.8271)	(0.8318)
Mom	0.0213***	0.0282***	0.0148***
	(0.0039)	(0.0039)	(0.0039)
Year F.E.	YES	YES	YES
Adjusted R^2	0.007	0.059	0.012
N	81,906	81,906	81,906

Table A1: Correlation

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	onetime	1.00														
2	sip	0.46**	1.00													
3	ret_rf	0.16**	0.31**	1.00												
4	age	0.11**	0.15**	-0.09**	1.00											
5	male	-0.06**	-0.08**	0.03**	-0.06**	1.00										
6	ndays	0.05**	0.15**	-0.80**	0.02**	0.02**	1.00									
7	income	0.07**	0.09**	0.18**	0.11**	0.02**	-0.26**	1.00								
8	married	0.07**	0.13**	0.04**	0.48**	-0.09**	-0.12**	0.10**	1.00							
9	Private_sect	0.001	0.07**	0.17**	-0.01**	-0.01**	-0.28**	0.27**	-0.01*	1.00						
10	public_sect	0.06**	0.03**	-0.03**	0.001	0.01**	0.13**	-0.04**	0.04**	-0.64**	1.00					
11	professional	-0.02**	-0.06**	-0.07**	-0.003	0.01**	0.08**	-0.04**	-0.01**	-0.26**	-0.03**	1.00				
12	Housewife	-0.02**	-0.02**	-0.08**	0.04**	-0.15**	0.08**	-0.14**	0.04**	-0.19**	-0.02**	-0.01**	1.00			
13	business	-0.03**	-0.03**	-0.09**	0.02**	0.05**	0.11**	-0.14**	0.03**	-0.46**	-0.06**	-0.03**	-0.02**	1.00		
14	retired	0.01**	-0.02**	-0.05**	0.16**	0.01**	0.03**	-0.04**	0.03**	-0.15**	-0.02**	-0.01**	-0.01**	-0.01**	1.00	
15	student	-0.04**	-0.09**	-0.08**	-0.13**	0.03**	0.12**	-0.27**	-0.15**	-0.27**	-0.04**	-0.01**	-0.01**	-0.03**	-0.01**	1.00

Table A2: Definition of Variables

Variable	Description	Source
User	An applicant to the Robo advising platform who has funded his/her account	Proprietary data from a Robo advisory firm in India
One-time	An indicator variable which is equal to one if a client makes on-time investment in the account	Proprietary data from a Robo advisory firm in India
SIP	An indicator variable which is equal to one if a client makes systematic (mostly, monthly) investment in the account	Proprietary data from a Robo advisory firm in India
Diversification	Summarizes if the client's portfolio is distributed between equity, bonds, and liquid assets	Proprietary data from a Robo advisory firm in India
Age	Age of the applicant as disclosed on the application form at the time of opening the account	Proprietary data from a Robo advisory firm in India
Male	Dummy variable equal to 1 for male and zero otherwise	Proprietary data from a Robo advisory firm in India
#days	Number of days between the account creation and the date of the snapshot	Proprietary data from a Robo advisory firm in India
Income	Income of the applicant as disclosed on the application form at the time of opening the account	Proprietary data from a Robo advisory firm in India
Married	Marital status of the applicant as disclosed on the application form at the time of opening the account	Proprietary data from a Robo advisory firm in India
Private sector	Fraction of applicants that work in private sector	Proprietary data from a Robo advisory firm in India
Public sector	Fraction of applicants that work in public sector	Proprietary data from a Robo advisory firm in India
Professional	Fraction of applicants that are professionals	Proprietary data from a Robo advisory firm in India
Housewife	Fraction of applicants that are housewives	Proprietary data from a Robo advisory firm in India
Business owner	Fraction of applicants that are business owners	Proprietary data from a Robo advisory firm in India
Retired	Fraction of applicants that are retired	Proprietary data from a Robo advisory firm in India
Student	Fraction of applicants that are students	Proprietary data from a Robo advisory firm in India
North India	Fraction of applicants from northern part of India	Proprietary data from a Robo advisory firm in India
South India	Fraction of applicants from southern part of India	Proprietary data from a Robo advisory firm in India
East India	Fraction of applicants from eastern part of India	Proprietary data from a Robo advisory firm in India
West India	Fraction of applicants from western part of India	Proprietary data from a Robo advisory firm in India
Central India	Fraction of applicants from central part of India	Proprietary data from a Robo advisory firm in India
North East India	Fraction of applicants from north eastern part of India	Proprietary data from a Robo advisory firm in India
Lag CPI	Last year's level of inflation as measured by CPI	Handbook of statistics, Reserve Bank of India
Bank_Ins. Valueadd	Value added by banking and insurance services in each state	Handbook of statistics, Reserve Bank of India

Lag GDP Growth	Last year’s level of GDP growth	Handbook of statistics, Reserve Bank of India
Invested Capital	Amount of passive and active capital invested in each state	Handbook of statistics, Reserve Bank of India
Personal Loan	Amount of personal loan by the residents in each state	Handbook of statistics, Reserve Bank of India
Urban Popn.	Fraction of population residing in urban areas in each state	Handbook of statistics, Reserve Bank of India
Bank Deposit	Amount of bank deposits by the residents in each state	Handbook of statistics, Reserve Bank of India
mkt_rf	Difference between the return on emerging market index and the risk-free rate aggregated over the holding period for a given client.	Yahoo Finance and Investing.com
SMB	Fama-French size risk factor for emerging markets aggregated over the holding period for a given client.	Kenneth R. French’s website
HML	Fama-French growth risk factor for emerging markets aggregated over the holding period for a given client.	Kenneth R. French’s website
Mom	Carhart Momentum risk factor for emerging markets aggregated over the holding period for a given client.	Kenneth R. French’s website